ANALYSIS OF THE TREATMENT OF A BIOLOGICAL WEAPON SPREAD THROUGH A TRANSPORTATION NETWORK

THESIS

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Abstract

Biological weapons are one of the top five threats identified by the Department of Defense in the United States. While most people commonly associate weapons of mass destruction only with atomic bombs, biological agents still have the ability to inflict mass casualties and panic. By strategically placing bioweapon detection units, known as BioWatch, in various airports, a disease spread could be detected and mitigated before country wide dispersal of the disease occurs. Key cities to invest this program are investigated through network analysis of flight itineraries with large volumes of traffic.

In addition to analyzing an airport network, there is also the possibility that an attack could still succeed and infect a city. Should this occur, the current Center for Disease Control policy is to trace sources of infections and vaccinate people suspected of harboring the disease. Kaplan *et al.*, as well as others, have argued for mass vaccination rather than the trace policy. Kaplan *et al.*'s model is extended to consider policies to respond to potential outbreak scenarios.

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Michael V. MacAndrew

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ANALYSIS OF THE TREATMENT OF A BIOLOGICAL WEAPON SPREAD THROUGH A TRANSPORTATION NETWORK

1. Introduction

Background

The United States remains constantly vigilant of weapons of mass destruction (WMDs). These include chemical, biological, and nuclear weapons. As stated in the National Strategy for Countering Biological Threats, reducing the risk of biological weapons by preventing the use or acquisition by State and non-State actors is critical to national security (Obama, 2009). Biological agents include pathogens (bacteria and viruses), as well as biotoxins from living organisms, used against humans, plants, and or animals in an offensive manner (Department of Homeland Security (DHS), 2004). Biological weapons are the vector or delivery method used to disperse these agents in order to cause death, sickness, damage, and or fear. While germ warfare has been practiced for centuries, the United States did not truly invest time and energy into biological weapons until the 1950s, with the start of the Cold War (Guillemin, 2005).

As of the 1970's, the United States stopped producing biological weapons. However, the country has invested time, money, and effort into combating germ warfare. This was recently seen with the pursuit of the anthrax attack in 2001. The SARS outbreak in China in 2002 (Guillemin, 2005) and the ricin letters of 2013 have also raised additional concerns regarding biowarfare (Nuclear Threat Initiative, 2013). Currently, biological detection equipment (such as Biowatch and polymerase chain reaction (PCR)

based sensors) has been developed and deployed in major cities to minimize the impact of a disease outbreak (Zimmerman & Zimmerman, 2003).

One area that is particularly susceptible to a biological attack is the airline industry. Although a known major biological attack has not thus far been conducted on an airport or a flight, it is obvious with the September 11th terrorist attack that should an attack occur, in addition to any tragic loss of life, the airline industry will suffer significant financial losses. Even if a small attack occurred, where a dozen people were infected, the public fear of biological weapons could still result in panic and substantial financial losses as evidenced with the anthrax attack executed through the US postal service (Guillemin, 2005). In 2001, the U.S. government spent $15 billion in loans to sustain the air line industry (Makinen, 2002). In excess of $142 million was spent on decontamination with the anthrax attack (Shane, 2002). Aside from an attack at an airport, where people are in a hurry to travel to various places and potentially spreading an infection, another concern is the airplane itself. With recycled air flowing through the aircraft, it is possible that a terrorist attack could be launched through a single flight or a series of flights. The detrimental effect of such an attack would be the wide dispersal of the contagion and difficulty in tracking the origin of an outbreak.

Aside from monitoring airports, another concern is what to do in the event of a disease outbreak. While the Center for Disease Control (CDC) does have plans for containing outbreaks, they primarily involve a trace vaccination program; where patient contacts are used to "trace" the transmission. Although others have argued for a mass vaccination program, in the event of a disease outbreak, this may not be an ideal strategy due to the logistics, vaccine availability, and limited protection from future outbreaks. A

compromise of the two strategies could involve pre-vaccination of a portion of the population.

Overall, this research has potential value to national security. According to the National Strategy for Countering Biological Threats, the release of a malicious contagion could "risk the lives of hundreds of thousands of people" (Obama, 2009, p. 1). Furthermore, the U.S. government acknowledges that an attack could "overwhelm our public health capabilities" and that "the economic cost could exceed one trillion dollars." Finally, even though "it is feasible to mitigate the impact of even a large-scale biological attack upon a city's population," the potential to spread a contagion to multiple population centers could exacerbate the costs and logistics needed to protect the public (Obama, 2009, p. 1). The loss of life could be catastrophic. The 1918 Spanish Influenza epidemic killed at least 50 million people worldwide (Taubenberger & Morens, 2011), in a time when contagions were not as mobile. While the economic impact was somewhat hidden in the costs of a world war, such a loss of life would have a massive and costly psychological and economic impact.

Problem Statement

The problem investigated in the study has two key thrusts. First, how might an attack use the airlines to spread an infection through the U.S.? Which cities might be most vulnerable and susceptible to be used for such attacks? Insights might suggest where more intense vigilance might be necessary. The second thrust is what might be the impact of such an attack on a city? What would be the estimated death rate when various pathogen characteristics are used, coupled with various public policies?

Problem Approach

By studying flight paths with the most amount of traffic, key airports can be determined in order to detect and mitigate a mass infection. These airports serve as ideal locations for disease spread nationally and should be equipped with biodetection units if they are not already equipped. They also should be given heightened attention if an attack is anticipated or progresses. Using data from the Bureau of Transportation statistics, a network was created and used in this study to model worst case scenarios (in this case, flight itineraries) for disease spread. While a simulated run using random connections can be acquired, this model focuses on passenger traffic volume to select the most disruptive flight path to compromise. This is done by optimizing flight itineraries and cascading networks. The aim of modeling these biological attacks is to identify key airports with the potential to create outbreaks in multiple cities. Furthermore, by equipping these airports with biodetection units, the US can strengthen its ability to detect and mitigate a biological attack.

If detection fails and an outbreak still occurs, a disease spread model is used to determine the outcomes of a biological attack in areas that could place the military and or large cities at risk. By analyzing the spread, an alternative solution to either the trace or mass vaccination programs can be acquired. This could potentially save lives, reduce economic costs, and mitigate the impact of a bioattack (Obama, 2012). In order to study the containment of an outbreak, modifications are made to an existing model based on a set of differential equations used to study disease spread (Kaplan, Craft, & Wein, 2002). This model is also parameterized to allow other diseases with similar transmission vectors to be considered. Finally, various parameters are adjusted to identify key traits

that could be adjusted for a worst-case scenario attack. Using these equations, several scenarios are run with various levels of pre-vaccination involved. By comparing the number of people infected, waiting in line for vaccinations, and dead, different mitigation policies can be analyzed, including mass, trace, and pre-vaccination programs.

Assumptions

This thesis assumes that any city that has been announced to have the BioWatch program also means their respective airport(s) utilize the program as well. In addition, this thesis assumes that if a BioWatch unit is equipped and the disease is in the registry, it is able to detect the weaponized disease within an hour. While this may not be realistic, the logistics of the BioWatch program are classified. The simulated itineraries also assume that a terrorist infected with a disease will infect a significant portion of the flight and that their goal is mass infection, without detection while the attack is being conducted. Furthermore, it is assumed that the carrier will survive the entire flight without succumbing to their infection or raising any alarms that would mitigate the attack. In addition, flights will operate on time and only one hour layovers occur. Since many business travelers seek flight options with this constraint, it is considered a reasonable simplification for the model. Even if these assumptions are considered optimistic on how the air traffic system functions, they provide a base to impute the impact of a flight system based attack.

Research Scope

The network analysis using flight itineraries have some limitations. While analysis primarily focuses on the volume of traffic between airports, it could be used to

estimate the potential number of people infected on a flight. This model does not select flights going to airports based on the airport's size, net flight traffic, or number of connections to other airports. This is done to help simplify the model and avoid prioritizing different measures. In addition, due to the numerous assumptions that would be needed, the model does not consider the distribution of an infection through various airport terminals.

With regards to modeling the CDC's response to a disease outbreak, the model in this research allows for parameters to be changed in order to better simulate various disease outbreaks. Although the equations could be modified for diseases spread by other vectors (such as insects), this model strictly focuses on diseases spread from person to person. It can estimate the number of people infected, dead, and in line for vaccinations in a closed population (i.e. a city). It does not determine the effects of a constantly changing population, nor can it account for the spread of an infection to other cities. The model does not predict the logistics needed to get vaccines to an area, the efforts needed to decontaminate buildings, nor does it determine human behavior during an outbreak.

Overview

Although the U.S. has taken measures to mitigate the effects of a biological attack, additional precautions can be made. With this in mind, the purpose of the network models are to simulate worst case scenarios in order to determine which airports should be equipped with biodetection equipment. By identifying key airports needed for detection, a potential infection can be stopped before highly trafficked routes are compromised. As for the CDC response, the purpose of the model is to approximate the

likely outcome of a disease outbreak and find effective levels of pre-vaccination to mitigate the spread. By using both these models, the effects of a biological attack using known agents can be detected quickly and mitigated, while minimizing the potential spread of an infection.

The remainder of the thesis is organized as follows. Chapter 2 focuses on literature pertaining to biological weapons, BioWatch, and previous studies conducted. The methodology in Chapter 3 explains the procedures used to build the new models. It also explains how the models are executed to get results needed for analysis. The Results and Analysis, Chapter 4, presents the outcomes of the network analysis and disease spread models. It also involves a few applications to demonstrate the value of the models and analysis conducted. Finally, Chapter 5 reviews the conclusions of the study and discusses the results and areas for future research.

2. Literature Review

Introduction

This literature review, while not all inclusive, reviews the key aspects needed for the modeling of contagions. In order to minimize the spread of an infection, several items must be addressed. First and foremost are the characteristics of a biological agent and how they spread. Next, preventative measures and previously conducted studies are reviewed. Finally, information on networks and Markov chains is presented to provide the necessary background for understanding the foundation of the models used.

Characteristics of a Biological Agent

There are several unique features to biological agents, which distinguish them from chemical and nuclear weapons. The first is the time delay. In a chemical or nuclear attack, once the attack occurs, the effects are rapidly obvious. With a biological attack, however, a person can be infected with a virus, bacteria, or toxin and not realize it for days after the attack. The second unique feature is the potential to spread a biological agent. Although many biological agents, especially toxins, cannot be spread from person to person, there is a subset of diseases, such as plague and smallpox, which are easily transmissible. This means that after an attack, which exposes members of a population, the agent can still spread and affect an entire population. This is significantly different from chemical and nuclear attacks, which can only harm those within a certain radius (or downwind) of the attack. Another feature is the fact that harmful pathogens occur naturally, making many of them easily accessible. So long as a terrorist has a source for a disease, a simple offensive biological program could be inexpensive (Burke, 2010). This

makes biological weapons an equalizer, where non-state actors and third world countries can conduct effective attacks on first world nations (Owens, 2009).

There are several characteristics that are unique to biological agents, which help classify them. One of these characteristics is the incubation period. The incubation period is how long it takes the disease to reproduce within the human body in order for its host to be infectious and able to pass the disease. This trait is important since it helps determine how fast a disease spreads. If a disease requires an incubation period of 4 days as opposed to 10, the disease will be able to spread faster. While a shorter incubation period may be appealing due to its faster spread rate, a longer incubation period means a biological weapon attack can be harder to initially detect and trace its transmission.

An additional important feature is how it spreads. This is important since not all biological agents can spread from person to person; some diseases can only spread by insect (such as malaria) or inhalation of spores (such as anthrax). Furthermore, for those biological agents that can spread from person to person, the method in which the disease spreads can differ. For example, some diseases can only be spread by fluids, such as Ebola, while others can be spread while talking to an infected person within several feet, such as smallpox (DHS, 2004).

Finally, a key factor is the type of biological agent and treatment available. Not all biological agents have approved vaccines available. Furthermore, treatments for bacteria, viruses, and toxins differ amongst each other (Fong & Alibek, 2005).

Vaccines

In order to reduce the susceptibility of the population, the CDC is working on various vaccines and treatments against harmful pathogens. Although a vaccine for every known biological agent does not exist, more than a dozen new drugs are under development and testing (DHS, 2004). Aside from having a vaccine available, there are other concerns that create a problem when mass vaccination is considered. For example, not every vaccine is guaranteed to be effective or without potential side effects. Although the efficacy rates for vaccines are relatively high, there is still a chance a person can become ill or even die from a vaccination. In addition, certain people cannot receive vaccines. This includes people who could have an allergic reaction to a vaccine depending on the materials used to produce it, as well as those too young, old, or sick to receive a vaccine. People who have a disease or are undergoing treatments that weaken or compromise their immune system, as well as pregnant women, could be prohibited a vaccine as well for safety reasons (CDC, 2007).

Aside from creating and delivering a vaccine, there are additional issues, such as mass production and delivery. Although vaccines can protect the public, unless the CDC has enough vaccines accessible, an outbreak may not be effectively suppressed. This is especially concerning if a particular vaccine takes time to produce. Another issue includes storage of the vaccine and shelf life. Timing is an additional concern. Not all vaccines are useful once a person is infected. If the body takes time to build up immunity or if the biological agent has progressed far enough, a vaccine may be useless for some victims during a biological attack.

One major concern in preventing the spread of diseases is the public's reaction to vaccines. While most people see the value and purpose of vaccines, there have been issues of skepticism from the public. Most of the skepticism stems from religion, rare complications, and parent concerns over a refuted study suggesting vaccines can cause autism. In addition, diseases that have a low probability of occurring may not justify vaccination. For example, according to the Citizens for Healthcare Freedom, 1 in 1,750 suffer an "adverse reaction" from the DTaP vaccine, "while the chance of dying from pertussis each year is one in several million" (Zimmerman & Zimmerman, 2003, p. 22). On the other hand, some organizations may be wary of diseases, other groups like the American Council on Science and Health argue the vaccines are extremely effective. Furthermore, through aggressive vaccine programs, diseases such as smallpox have been eradicated worldwide while the number of victims of polio and measles have been significantly reduced (Zimmerman & Zimmerman, 2003). The military also uses vaccines in the unlikely event of a biological weapon attack, such as the release of smallpox.

Diseases of Concern

Several diseases of great concern are smallpox, Ebola, Marburg, Lassa, and plague. Smallpox is of great concern because it is an airborne, easily transmissible virus that can be spread from person-person just by breathing. There is a vaccine for smallpox available, but there are several issues that may be of concern. Most important is the fact the vaccine is effective for only 3-5 years. Although additional vaccines may be taken to increase the length of protection, immunity can only be extended. Another concern is how potent a vaccine is after a long period of storage. Currently the US has enough

smallpox vaccines (about three hundred million) stockpiled to inoculate the entire public in the event of an emergency. However, this stockpile may be useless in 20 years (since the vaccine involves injecting a live vaccinia virus into a person) (CDC, 2007) and the current stockpile already includes 60 million vaccines created prior to 2001 (Zimmerman & Zimmerman, 2003). There is also the possibility that the U.S. doesn't possess a tested vaccine for various strains of a disease. Currently, a vaccine from Europe (that has not been approved by the CDC yet) is being implemented to contain a specific strain of meningitis at Princeton University and University of California at Santa Barbara (Schnirring, 2014).

Viral hemorrhagic fevers, such as Ebola, Marburg, and Lassa are a great concern due to their potential to spread as well. Although these viruses require more contact with people (for example Ebola and Marburg must be spread via fluids), they can still create a serious problem for human health. A key problem with these diseases are the lack of effective vaccines. Finally, plague is a bacteria that can easily spread from person to person. If we consider the pneumonic form of plague, it is very similar to smallpox in its ability to spread from people just by talking. Unfortunately, the US does not have an updated vaccine for plague (the previously used one was discontinued in 1999) (DHS, 2004).

Although there are other biological agents, including, but not limited to, botulism, tularemia, anthrax, cholera, ricin, and encephalitis, these agents cannot spread from person to person. Therefore, should a person be infected with ricin, contact will not put others in harm's way (DHS, 2004). In addition, there are a handful of biological agents that have a low lethality rate but still present a threat. For example, a number of

encephalitis or arenaviruses will not kill a large number of people but will make them ill for a period of time. In the military, several pathogens that may create this problem include rotavirus, hepatitis A virus, PRD 1 bacteriophage, micrococcus luteus, and serratia rubidea, as identified in Air Force Manual 10-2503 (2011).

Although there exist lists of diseases that could be used as a biological agents, the list will never be complete given the ability to genetically engineer and crossbreed various pathogens. For example, with regards to bacteria, certain genes (such as antibiotic resistance) can be passed from one bacteria organism to another (Young, 2013).There is also the possibility of biohacking, where people can modify various strains of bacteria and viruses using lab equipment and various websites for information (Wikswo, Hummel, & Quaranta, 2014). It has also been reported by scientists such as Ken Abilek (former bioweaponeer for the USSR) that Russia has developed various weaponized strains of biological agents, as well as chimera agents (involving the combination of more than one biological agent). Unfortunately, until these unidentified strains are used in an attack, the U.S. will never be fully prepared to counter their effects. If detection equipment does not have a pathogen's "signature," it is even much less likely to detect the pathogen. In addition, while intentional bioattacks should be of concern, the possibility of a naturally occurring outbreak must be considered as well (Zimmerman & Zimmerman, 2003).

Spanish Flu

One example of a devastating disease spread was the Influenza outbreak of 1918, otherwise known as the "Spanish Flu." This incident was estimated to have infected a

third of the world's population (about 500 million at the time) and killed between 50-100 million people. The case fatality rate was at least 2.5%, which may sound small until compared to <0.1% case fatality rate of other influenza outbreaks. Additionally, half of the fatalities were people between the ages of 20-40. Should the disease return, the CDC estimates that an outbreak would kill at least 100,000 people across the globe (Taubenberger & Morens, 2011).

These characteristics are critical since a disease outbreak could easily impact the military. With the Influenza outbreak, there was a clear effect on the military. Based on the War Department's estimates, at least 26% of the Army (over one million men) at the time was infected with the Spanish Flu. Worse, 30,000 troops died prior to arriving in France to aid ongoing conflicts in World War I. Within the U.S. Navy, at least 35% (about 106,000 out of 600,000) were hospitalized and about 5,000 died (Department of Public Health, 2010).

Another major concern was the various rates of infection. While some areas, such as Camp Lewis, WA only had a 10% sickness rate, other locations such as Camp Beauregard, LA had a 63% sickness rate. Due to these high rates of infections, it was not uncommon for troops to go AWOL (absent without leave) in order to avoid getting sick once their base was compromised. Unfortunately, there are limitations on this data. While it is assumed the records from various base hospitals in 1918 are accurate, it is possible that the data is imperfect. In addition, only those who reported sick and received treatment were included in the data. Troops who went AWOL (absent without leave), did not report the sickness (or did not receive permission to get medical treatment), or reported sick while on leave were not included in the estimates. In addition, the data is

provided based on the 1918 records. Regardless, the Navy and Army both implemented quarantine measures, including face masks and isolation. These measures were ineffective due to the inability to properly quarantine bases during a time of war (Department of Public Health, 2010).

Clearly, diseases have a large potential to devastate a population. While quarantine measures can be set in place, it is still possible for a disease spread, especially in areas not ideal for quarantine (such as a military base in an active theater). If diseases can be detected, however, their spread may be mitigated.

BioWatch

Currently, there are various methods being used to detect for a biological attack. One of the most heavily relied on monitoring systems is BioWatch. Modern BioWatch equipment essentially relies on an air filtration system that runs 24 hours a day, seven days a week and is inspected for pathogens. The frequency of the inspections are classified and most likely vary depending on the volume of pedestrian/passenger traffic. Unfortunately, there are a few problems with this approach. The first problem is that a sample of the pathogen is needed in order to positively identify it when compared to an air sample. Therefore, should a hybrid pathogen be released in public, BioWatch may not detect it. The other problem is the Biowatch program has had issues of false positives, or falsely detecting a pathogen. From an emergency preparedness standpoint, it is better to have a false positive than to not report a positive sample. Confidence in the system's output, however, becomes less trusted if it is constantly setting off false alarms. A false alarm (or true alarm) may also cause a panic. The cost in money, time, and interruption of

traffic in order to close off a city, subway, or airport could create could a serious problems (Hodson, 2012).

Currently, BioWatch is known to be implemented in at least 31 cities, including Philadelphia, New York City, Washington, DC, San Diego, Boston, Chicago, San Francisco, Atlanta, St. Louis, Houston, and Los Angeles. The location of Biowatch equipment is not known to the public in order to prevent tampering with the system (Shea & Lister, 2003). While the BioWatch program is under the Department of Homeland Security's authority, its use could help the military.

General Services Administration

While the military has transport aircraft available, most personnel travel using airports close to their base. In order to save the military money, the U.S. government (specifically the General Services Administration (GSA)) has set up a program known as the Airline City Pair Program. This program aims to reduce the cost of travelling for members of the DoD between various cities located near bases. If a flight between two cities is highly travelled and included in the Airline City Pair Program, a biological attack could have widespread impact across multiple military installations. This would especially be problematic for cities located near multiple military installations. Another concern is if an airport has a number of flights that are used in the Airline City Pair Program. A large number of flights, especially if highly trafficked, could increase the potential spread of a biological weapon. In addition, since people often have to wait an hour or more prior to boarding a plane (whether it's the first flight or a connecting flight in an itinerary), the potential to spread a disease in an airport increases (GSA, 2013).

Based on the numerous opportunities to spread a disease, it is worth studying how a disease can spread. This can range from modeling the actual spread of disease amongst a population to looking for ideal areas for an infection to start. Luckily, various independent researchers and the CDC have conducted additional analysis to minimize the impact of a biological attack.

Prior Research and Analysis: Vaccine Analysis

Numerous studies have been done with regards to the spread of diseases and how to combat them. Kaplan, Craft, and Wein, argue in favor of fully vaccinating the population in the event of a smallpox attack (Kaplan *et al.*, 2002). In their paper, they use Markov chains and supporting differential equations in order to determine the number of people infected, in a vaccination queue, and dead from an attack.

To respond to this attack, two methods are considered. The first is a trace vaccination program, which the CDC currently utilizes. In the trace vaccination program, those with symptoms are reported and a list is generated that involves tracing all the people that have had contact with known infected individuals. As people are added to the list, they are tracked, vaccinated, and questioned about additional contacts. The second method, which Kaplan *et al*. (2002) supports, is to vaccinate the entire population once an outbreak is determined (CDC, 2007).

To illustrate Kaplan *et al*.'s (2002) results, Figure 1 is included from their paper

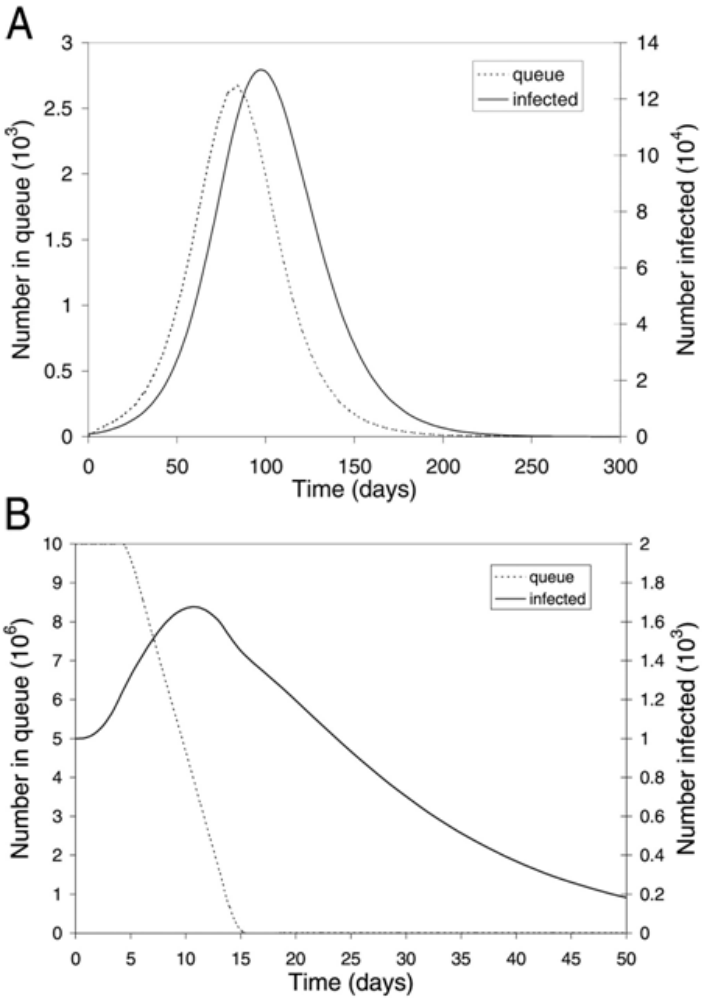

Figure 1. Kaplan *et al*. Model Results (Kaplan *et al.*, 2002, p. 10936)

Figure 1 displays two charts. Graph 1A displays the results of the trace vaccination program. The noticeable features on this graph are a peak number infected of about 2,500 people in the queue around day 75 and by day 100, the number of infected is estimated around 130,000. In addition, the time scale on the graph extends beyond 150 days to contain the outbreak. If the results of graph 1B are studied, it is clear that the number of people in the queue is extremely high since the program calls for vaccinating everyone in

the city population of ten million. However, the peak infection number is about 1,700 by day 12 and containment is achieved within two months based on the graph.

With regards to the calculated outcomes of these two strategies for handling an outbreak, Kaplan *et al*. (2002) clearly demonstrates that a mass vaccination plan would significantly decrease the number of deaths (by about 90%). In the mass vaccination program, Kaplan *et al*.'s (2002) model and equations calculate that in a span of 10 days, the entire city population (of ten million people) can be vaccinated with an outcome of 1,830 people infected and 560 deaths. This plan would require 690 isolation units to quarantine those who are febrile and infectious (Kaplan *et al.*, 2002).

In the trace vaccination program, however, the estimated number of infected is 367,000 with 110,000 deaths. The trace plan would also require 59,000 isolation units. However, one caveat that should be mentioned is the condition Kaplan *et al*. (2002) provide. The trace vaccination program estimates vaccinators issuing 50 vaccines a day while in the mass vaccination program, vaccinators issue 200 vaccines a day (based the mass vaccination of New York City in 1947 due to an outbreak of smallpox). Another noticeable assumption is that people are vaccinated throughout the day. This is probably done in order to simplify the model. However, it is possible that vaccines could be administered 24 hours a day in order to trace and contain a deadly outbreak like smallpox quickly (Kaplan *et al.*, 2002).

If one considers Kaplan *et al*.'s (2002) work, although mass vaccination should effectively contain an outbreak, it is assuming the current stockpiles of vaccines are readily accessible and still effective. If one tried to vaccinate the entire public today, this

protection would be virtually ineffective in five years unless people applied for additional vaccines.

Another study was conducted on the effects of quarantine and vaccines. Meltzer, Damon, LeDuc, and Millar used Markov chains based on recorded European outbreaks of smallpox to determine an appropriate response to dealing with a smallpox outbreak (2001). In their research, they considered the effects of using only a vaccination policy, a quarantine policy, and a combination of vaccinations and quarantine. Based on their results, they determined that a combined approach of vaccines and quarantine would be the best option in terms of minimizing deaths.

Prior Research and Analysis: Network Analysis

Aside from vaccination programs, a number of studies regarding airport vulnerabilities to disease spread have also been conducted. One study is by Conti, Cao, and Thomas, uses data from the U.S. Bureau of Transportation Statistics to determine the most critical airports to attack in order to disrupt the air travel network (2013). Based on the network created, the authors identified the top five airports utilizing various scores, such as the number of cities an airport is connected to and the volume of traffic.

In Table 1, one can see that metrics in network analysis, such as closeness and betweeness, were implemented (using data from the Bureau of Transportation Statistics) (Conti *et al.*, 2013). These metrics are on a scale of zero to one, where a higher score is preferred. For closeness, the score is based an airport's connection to all other airports in a network. A higher score indicates that an airport has better access to other airports and can connect to more locations in one flight. A lower score, on the other hand, implies that

an airport is not in an accessible location and must use more than one flight to get to other airports in the network. The betweeness score measures how frequently an airport is used to connect to other airports. The score is based on the percentage of time an airport is used in a shortest distance problem between two other airports). An airport with a high score indicates that it is in a key location and must be used to get from one airport to a different airport quickly (Conti *et al.*, 2013).

Table 1. Example of Conti *et al.*'s Metrics Used (Conti *et al.*, 2013, p. 3)

Top 5 Closeness		
Rank	*Airport*	*Score*
1	Denver International	0.4848
2	Ted Stevens Anchorage International	0.4838
3	Memphis International	0.4815
4	Minneapolis-St Paul International	0.4813
5	Hartsfield-Jackson Atlanta Inter.	0.4806
Top 5 Betweeness		
Rank	*Airport*	*Score*
1	Ted Stevens Anchorage International	0.3538
2	Seattle/Tacoma International	0.0873
3	Denver International	0.0757
4	Fairbanks International (Alaska)	0.0684
5	Minneapolis-St Paul International	0.0456

Once these metrics (plus several scores created by the authors that rely on the volume of traffic and number of connecting flights) were combined, they determined the most critical airports (shown in Table 2).

Table 2. Conti *et al.*'s Results (Conti *et al.*, 2013, p. 4)

Most Important Domestic Airports (In No Order)
Denver International
Ted Stevens Anchorage International
Seattle/Tacoma International
Minneapolis-St Paul International
Hartsfield-Jackson Atlanta International
Chicago O'Hare International

Another study done by Nicolaides, Juanes, Gonzalez, and Cueto-Felguerso from MIT's Department of Civil and Environmental Engineering used networks to determine the most influential airports for disease spread by considering location and connectivity (2012). In their study, the busiest airports were not necessarily the most critical for disease spread. Honolulu International Airport, for example, was ranked as the third most critical airport for disease spread. This is primarily due to the large number of flights that rely on Honolulu in order to transport passengers from Southeast Asia and other Pacific nations to the U.S. or vice versa. While it was not studied in the report, this could be detrimental to US forces going overseas; especially considering the use of civilian airports in Asia (Nicolaides *et al*., 2012).

Additional Analysis and Concerns

One other concern regarding disease spread is "Airport malaria." Airport malaria occurs when a person contracts malaria in an area not known to house the disease. This is possible when a mosquito with the disease is transported via international flight to a foreign area. Once transported to a new habitat (where malaria is a not a typical concern), the mosquito is able to infect others and create a serious concern for health officials.

While some basic probabilities and models have been developed, the primary concern is the spread of an insect vector, such as a mosquito, through international airports. Although this study only focuses on diseases spread by people, it is possible for a disease vector like insects to spread from one area to another (American Society of Tropical Medicine and Hygiene, 2008; Isaacson, 1989).

Although various mathematical models can provide an estimation of worst case outcomes of an attack would be, there are a number of limitations to these models. For example, disease spread does not stay constant regardless of the person infected. Depending on a variety of factors, including overall health and how social a person is, two people may spread a pathogen at completely different rates. Generally, the time it takes a pathogen to incubate and proceed through it stages, as well as the number of people one infected person comes into contact with while contagious, can vary drastically. This forces models to rely on either averages or probability distributions, which can only give a general idea of how a disease will spread.

One can run into other issues when modeling response measures as well. For example, although a vaccination and quarantine policy may be effective in limiting the spread of a disease, it is possible that the public may not cooperate or act in a calm, rational manner once an announcement is made about a biological attack. Furthermore, most models assume a closed population (in other words, no people can enter or leave the city, causing further casualties and spread vectors). If the disease has been spread through a transportation system, this could definitely be problematic when the incubation period ends.

Network Analysis

As implied in Conti *et al*. (2013), as well as the research done by Nicolaides *et al*. (2012), there are methods to evaluate key airports using network analysis. Essentially, a network consists of a collection of nodes and arcs, where the nodes are central points and the arcs connect various nodes. For an airport network, the airports serve as the nodes and the flights that connect the airports act as arcs. These networks can be structured as matrices, where each airport is assigned a row and column.

In addition to building a network, additional information can be contained in the network. For example, the total number of passengers or the average number of passengers travelling between locations can be included within the arcs. Rates of infection can be treated as a flow, where branches with higher traffic may be more valuable to network (Ahuja, Magnanti, & Orlin, 1993).

By focusing on connecting flights, less focus is given to the airports themselves, as done in prior analyses. In this version of the network analysis, branches are assigned a flow (such as number of passengers) and the objective is to maximize the flow by travelling through certain flights (Hamill, Deckro, Wiley, & Renfro, 2007). Furthermore, with the ability of diseases such as smallpox to spread easily to people within six feet of the infected person, combined with the recycled air circulating through an aircraft, focusing on flights (as opposed to airports) is an ideal strategy for a terrorist attack (Fong & Alibek, 2005).

Cascade Networks

Another model that is considered is the network cascade model. In this model, various nodes are connected to one another. However, should one node be infected, it does not necessarily mean all other nodes the infected node is connected to may be compromised. In the cascade model, a certain threshold is specified before a change in the node is indicated. In terms of a social network, one person may not change their behavior until a certain number of friends have influenced them by changing their behavior (Kleinberg, 2007). For an airport, the same cascade model could be applied, where an airport is compromised once a specified number or percentage of infected passengers have arrived from various compromised airports to a susceptible one.

Due to the incubation periods of diseases, such a scenario is less likely. For a disease such as smallpox, once a person is infected, it takes about 10 days for the virus to incubate before the virus can spread to other people (Fong & Alibek, 2005). For diseases such as Ebola (and even less deadly ones such as norovirus), which have shorter incubation periods of one to two days, the cascade network does not seem like a possible option for modeling an outbreak. This is especially due to the fact that Ebola can only be transmitted via fluids and a terrorist coughing up blood on passengers is likely to raise some alarms immediately. Although it is not addressed in this study, diseases with a short incubation period could potentially be effective on cruise line networks (due to the time lag between ports).

A more meaningful application of a cascade network involves the study of diseases passed by touch, which does not require humans as a major vector. This would include the diseases mentioned in Air Force Manual 10-2503 that serve more as an

inconvenience than a lethal attack (2011). Although such an attack could weaken key units at critical times if properly planned and coordinated. Ideally, the disease would spread by people touching surfaces such as seats, handrails, doorknobs, and so forth. Once those surfaces are touched by others, the disease can continue to spread. While it would not severely compromise a person and potentially kill them, such as smallpox, a disease that can survive and replicate outside a living host could spread rapidly. This type of spread could be modeled effectively using a cascade network. In addition, this type of disease would also be effective against troops or garrisons in a daily unit transport (Fong & Alibek, 2005).

Markov Chains

Aside from network analysis, Markov chains are also critical for this study. In the Kaplan *et al*. (2002) model, differential equations are used to quantify the rate of change from one state to another. For example, the author provides equations for the rate of change from a susceptible period to an infected period. This change from one state to another, which provides the basic layout of the model, is known as a Markov chain. Although Kaplan *et al*. (2002) provided the equations for the rate of change from one state to another in the model, the states are treated as part of a Markov model. Using this set, percentages can be used to determine the fraction of a population that succumbs to a disease and those that recover (Ross, 2007).

While additional Markov chains are not the focus of this research, there has been a substantial amount of effort placed into using this method for diseases analysis. The most basic and well known models are the susceptible-infected-susceptible (SIS) and

susceptible-infected-recovered (SIR) models. In these models, the population is broken up into states. Those who are infected are in the "I" state while those in the "S" state are susceptible. Additional states can also be added as needed. For example, a recovery state, known as the "R" state, is used in the SIR model. In these Markov chains, as time progresses, people shift from one state to another and estimates of infection numbers can be determined. However, these simplified models have a limited use and can be complicated as more states are incorporated into the method (Dodds & Watts, 2005) (Allen & Burgin, 2000). Essentially, the Kaplan *et al*. (2002) model is a complex version of an SIR model with additional states for death and vaccination queues.

Design and Analysis of Experiments

Design and analysis of experiments (DOE) is a statistical method which determines significant variables and their effects on a desired output. This involves modifying either one variable at a time or a combination of variables and determining the impact of the change. While a model can be re-run multiple times to determine the sensitivity of a response to a specific set of parameters, DOE allows for key variables to be identified. Furthermore, using statistical analysis, linear regression can be used to determine the range of outcomes and key variables in the model. In order for linear regression to work, it is assumed that the distribution of the errors is normal, the errors are independent, and constant variance is observed (in other words, there is no trend in the errors). Since the data points are provided from a model with different settings, the errors are independent. The normality and constant variance assumptions depend on the results of the linear regression model (Montgomery, 2013).

Conclusions

Clearly, biological agents are a threat to national security. Furthermore, diseases that can spread from person-to-person contact are of extreme interest due to their potential to spread amongst a population, especially in heavily trafficked areas. While vaccines and the BioWatch program are in effect, the US is still susceptible to attacks. Although several studies have been conducted on mitigating these attacks, more analysis can still be performed. This includes considering alternate options for dealing with an outbreak as in the Kaplan *et al*. (2002) model and shifting the focus from airports to flights in a network analysis of the airline industry. The methodology incorporates this information and constructs the necessary models needed to identify key airports and analyze disease spread.

3. Methodology

Introduction

This chapter presents the methodology used to execute the analysis presented in this thesis. Building on the literature review, there are methods to evaluate disease outbreaks using differential equations and network analysis. In order to perform these evaluations, a network must be constructed to model the flights and traffic between various airports in the US (as shown in Figure 2 and Figure 3). This model is then used to suggest potential effective itineraries to execute the attack. In addition, the Kaplan *et al*. (2002) model was extended to evaluate alternate approaches to their disease spread model.

Figure 2. Airports in US (Department of Transportation, 2012)

Reviewing Figure 2, it is clear that modeling an airport network within the US and its territories is a complex task. Certain airports are more frequently used than others and serve as key nodes in a network. To further illustrate this, Figure 3 highlights the actual airport network the MIT study produced (Nicolaides *et al*., 2012). In this figure, key airports are indicated with full circles around the airport. While the study by Nicolaides *et al.* (2012) included flights to other countries, this thesis only focuses on flights within the United States and its territories (to include Guam, Puerto Rico, and the Virgin Islands).

Figure 3. Visual of Airport Network in US (Nicolaides *et al*., 2012)

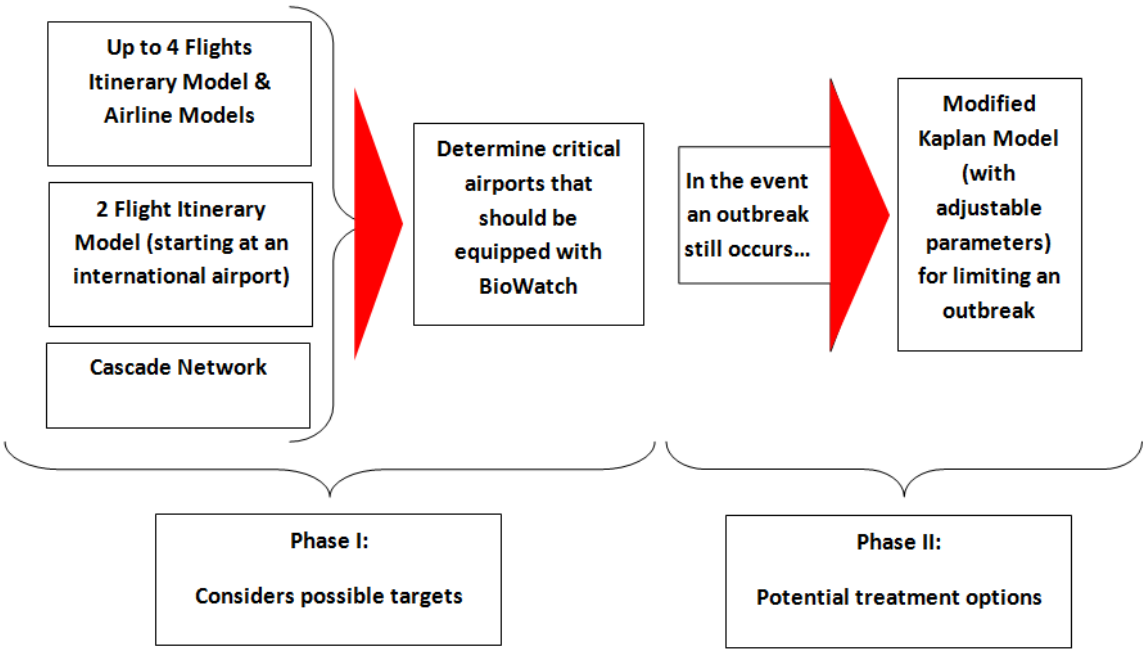

Figure 4. Problem Framework

The thesis covers two approaches for dealing with a biological weapon attack. As shown in Figure 4. Phase I determines critical airports for detection using network analysis of flight itineraries and cascade networks. Should an outbreak still occur, Phase II is used to analyze an alternative treatment for containing an outbreak to mass or trace vaccination.

Phase I

The goal of Phase I is to determine which airports should be equipped with BioWatch (if they are not known to have the detection equipment). This is done using three different network scenarios shown in Figure 5. The first two approaches involve

flight optimization and the third approach involves cascade networks. All network analyses rely on the data from the U.S. Bureau of Transportation Statistics.

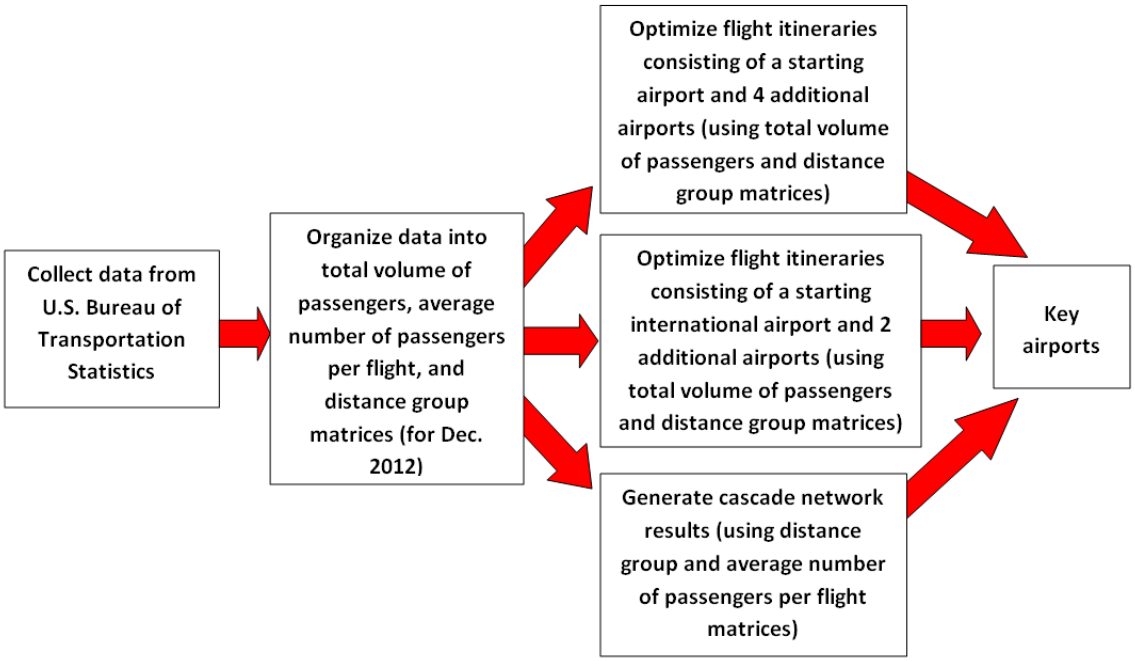

Figure 5. Phase I framework

Data

In order to analyze the spread of a disease through a transportation network, a similar study to Conti *et al*. was conducted (2013). Using the same information source as Conti *et al*., a network is formed using the data from the Research and Innovative Technology Administration (from the Bureau of Transportation Statistics (2013)).

The data that was imported included the number of passengers, the number of flights, the distance between airports, the airline, the origin airport, the destination airport, the distance group, the aircraft group, type, and configuration. The distance

group refers to grouping by flight the distance in increments of 500 miles. Thus, if the distance between two airports was 0-500 miles, it was in the first group, if the distance between the airports of 501-1000 miles, it was in the second group, and so on. The distance group was also used as a proxy for time. Flights in distance group 1 are assumed to take one hour to complete, flights in distance group 2 are assumed to take about two hours to complete, and so on. Although weather and traffic congestion can impact the time it takes to complete a flight and rounding can affect the total flight time, using the distance group to approximate flight time simplifies the data. Furthermore, the data for various flights between two airports supports this assumption. The aircraft group and type refer to the plane used for the flight. For example, group would classify the plane based on the number and type of engines used (such as a 2 engine jet) while type would specifically refer to the aircraft (such as a Boeing 717-200).

Due to file size, the data used in this study consisted of all flights only in December 2012. Although data consisting of flights throughout the year would give a more accurate representation of traffic, December typically tends to be one of the busier months due to holiday travels. In addition, the public tends to let its guard down during the holidays, making it an ideal time for a bioterrorist attack (Bureau of Transportation Statistics, 2013).

In order to help consolidate the data and produce more consistent results, a portion of the observations were omitted. For example, all observations where the passenger number was zero were eliminated. In addition all flights not marked as "passenger configuration" were eliminated as well. Planes not so designated meant the plane was not designed to carry people. While these entries could be useful for biological

attack through the postal service (similar to the anthrax attack of 2001), terrorists infected with a disease will obviously infect more people (and thus create more panic) by utilizing passenger flights available to the public. Finally, any flights listed with a zero for time or distance travelled (indicating the plane did not leave the airport probably due to mechanical issues or weather), were eliminated as well.

Once the data was acquired, each airport was treated as a node and the flight connecting two airports were treated as arcs. By organizing the data into a matrix, a network can be analyzed. The number of airports considered in this research was 700.

Notional Construction of a Network with Passenger Flow

In order to understand how the matrix and network were set up, this example illustrates the approach. Using Table 3, a mock flight scenario is constructed. In this case, the number of people travelling from City A to City B is equal to the number of people travelling from City B to City A. For example, the highlighted number indicates that 300 people travelled from City A to City C in a month by Figure 6. While only symmetric passenger traffic were used in this example (A→B = B→A), asymmetric traffic are incorporated in this research (A→B≠B→A).

Table 3. Example of an Airport Matrix (using volume of traffic) per month

	City A	City B	City C	City D	City E
City A	0	800	300	500	0
City B	800	0	600	0	0
City C	300	600	0	0	0
City D	500	0	0	0	80
City E	0	0	0	80	0

Using Table 3, the network in Figure 6 can be formed. Likewise, if Figure 6 was initially provided, Table 3 could be created.

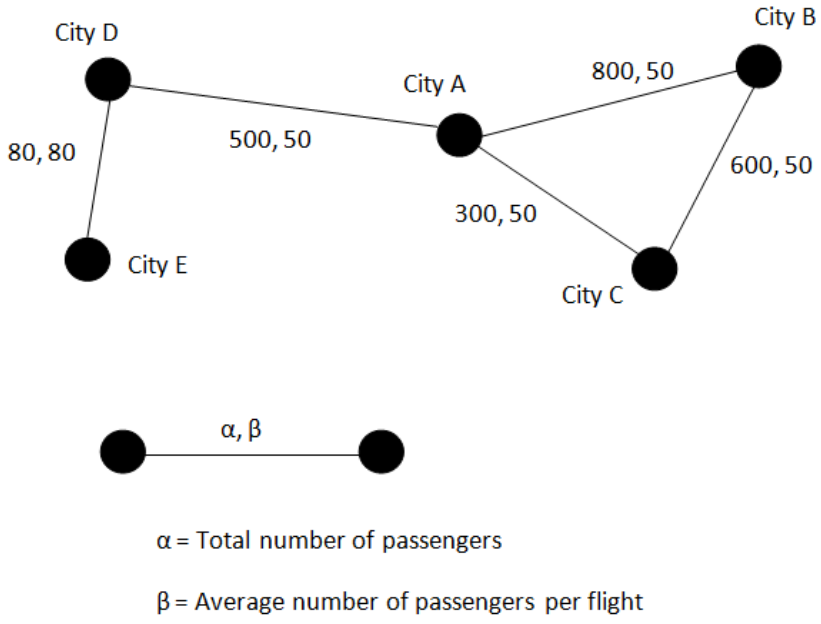

Figure 6. Example of an Airport Network

In order to measure the volume, one could look at the average number of passengers per flight or the net traffic of passengers. While using the net volume of traffic between airports would not provide an exact estimation of the number of passengers, the benefit is that the model focuses on highly travelled routes. This is critical since airplanes are not thoroughly cleaned between flights. This provides a chance for additional infections after the infected passenger has left. There is also the possibility of creating widespread fear and mass disruptions by infecting highly travelled routes. Consider the example in Figure 6, attacking a flight going from City B to City A would be beneficial from a terrorist's point of view since it is a frequently travelled route. Thus, attacking the flight may yield a large number of victims. However, while an attack on the flight from

City B to City A is appealing due to the large volume of traffic on that leg, a flight itinerary from City B to City C and then to City A may be more effective since a bioattack would compromise half the network nodes and disrupts a larger volume of passengers. Regardless, if City A is exposed and closed down, one can see how easily the network is compromised.

Aside from the benefits of looking at network traffic, there are also some problems to consider with the average number of passengers per flight. One problem is that a flight that has a high number of passengers per flight may not be travelled often due to limited service. The trouble with this is a route not travelled frequently will not create mass disruption in an airline network attack. For example, if one looks at the Figure 6, selecting the flight with the maximum number of passengers per flight would immediately dictate that an attack be conducted on the flight between City D and City E. While this attack could instill fear, an attack on a flight going to City A would likely cause a larger disruption in the network. As one can see, with the frequent flights and large volumes of passengers going through City A, an attack on a plane going from City D to A would potentially do more damage to the network. Furthermore, flights that are offered daily are more appealing since they can be booked at an ideal time and offer more opportunities to conduct an attack. If a terrorist with smallpox who is infected is trying to maximize their flight time, they will likely purchases tickets for flights that are easily available (and most likely fly daily). In any event, the model can be adjusted to consider either averages or specific flight data if available.

Flight Optimization

In order to find the flight path with the largest volume of passenger traffic, itineraries starting at each airport were generated. Mathematically, the construction of flight itineraries would be as follows:

$$Maximize\ X_{a,b} + X_{b,c} + X_{c,d} + X_{d,e} \quad \textbf{(1)}$$

where $X_{\cdot\cdot}$ is the volume of traffic between two airports, a is the starting location, b is the first stop, c is the second stop, d is the third stop, and e is the fourth stop. The constraints would be the following (T_{ij} is the time need to from airport i to airport j);

$$a \neq b \neq c \neq d \neq e \quad \textbf{(2)}$$

$$T_{a,b} + T_{b,c} + T_{c,d} + T_{d,e} \leq 18 \quad \forall\, a, b, c, d, e \quad \textbf{(3)}$$

$$T_{a,b}, T_{b,c}, T_{c,d}, T_{d,e} > 0 \quad \forall\, a, b, c, d, e \quad \textbf{(4)}$$

$$T_{a,c} + 3 > T_{a,b} + T_{b,c} \quad \forall\, a, b, c \quad \textbf{(5)}$$

$$T_{b,d} + 3 > T_{b,c} + T_{c,d} \quad \forall\, b, c, d \quad \textbf{(6)}$$

$$T_{c,e} + 3 > T_{c,d} + T_{d,e} \quad \forall\, c, d, e \quad \textbf{(7)}$$

$$T_{a,d} + 4 > T_{a,b} + T_{b,c} + T_{c,d} \quad \forall\, a, b, c, d \quad \textbf{(8)}$$

$$T_{b,e} + 4 > T_{b,c} + T_{c,d} + T_{d,e} \quad \forall\, b, c, d, e \quad \textbf{(9)}$$

$$T_{a,e} + 4 > T_{a,b} + T_{b,c} + T_{c,d} + T_{d,e} \quad \forall\, a, b, c, d, e \quad \textbf{(10)}$$

Equation 2 prevents the same airport from being used more than once. Equation 3 restrains itineraries to 18 hours and equation 4 is used to ensure all flights are connected (if no time is needed to get from airport c to d, for example, this implies c and d are not connected). Equations 5 through 10 are constraints used to generate effective itineraries

without raising suspicion (assuming the flight on the left side exists). Using Equations 5-7, for example, the 2nd stop airport cannot be right next to the starting point. For example, if a flight path consists of Colorado Springs, CO, Las Vegas, NV, and Denver, CO, the path should be rejected. While this itinerary could be possible, a flight from Colorado Springs to Denver takes an hour, which is significantly shorter than flying to Las Vegas and then to Denver. If a flight path consisted of New York City, Atlanta, and Miami, the path is acceptable since the time it takes to get from New York to Miami (plus three hours) exceeds the time needed to get from New York to Atlanta and Atlanta to Miami (with a one hour layover included). With regards to Equations 8-10, for example, the time needed to get from a starting location to the third or fourth stop directly (plus four hours to account for a longer itinerary) must exceed the time needed to travel the suggested route. Similar to Equations 5-7, this constraint prevents suspicious flight itineraries from being selected. This condition, as well as the other conditions mentioned, was determined through testing of alternative formulations. Essentially, the model tries to prevent unrealistic and or questionable flight itineraries from being selected. This allows the terrorist to avoid suspicion.

Preprocess

In order to conduct a network analysis, several matrices were created. Using the December 2012 data from the whole airport network, a matrix was created documenting the total volume of passenger traffic between airports during December 2012. The first column and row indicate specific airports (labeled using coded numbers (for example, Denver International is labeled 11292)). Next, any flight originating from Airport A to

Airport B would have the total volume of traffic for December 2012 indicated in the matrix. Specifically, the value would be placed in the row corresponding to Airport A's code and the column corresponding with Airport B's code. This was done for the total volume of traffic during December 2012 for the entire network as well as for each airline.

Based on the structure of the optimization function, a starting location with four airports is selected to create a four flight itinerary. Extra rows and columns were added to serve as terminating null airports. By including terminating null airports, this allowed a three flight itinerary with a fourth dummy flight to a terminating null airport to be selected as a flight path with a large volume of passenger traffic. This allows flight plans with fewer stops but more traffic to be included in the top itineraries (so long as the constraints are met).

These terminating null airports had several unique properties to ensure they could produce accurate results. First, any airport could connect to the terminating null airports. However, terminating null airports can only connect to other terminating null airports. This ensures that an itinerary must have connected flights. An itinerary generated by the model cannot have a passenger travel only three legs from City A, to B, then C. Second, there is no value for traffic flying into or out of terminating null airports and there is no layover time. By not having any traffic, terminating null airports are not likely to be selected when flight itineraries search for highly trafficked routes. In addition, by not including a layover time for the terminating null airports, the total flight time of an itinerary with a terminating null airport does not include additional hours flying to a null airport.

Since the distance group is used as a proxy for time, a distance group matrix was created. For this matrix, all entries with a value larger than zero (indicating a flight existed) had a one added to them. This essentially combines the layover time (assuming it is one hour) and the travel time to get to the next airport into one value. Even if a one flight itinerary is generated, the one hour layover included in the time estimate to get to the next airport corresponds to the minimum one hour needed to check in before a flight. This was needed to provide an estimate for travel time with each additional flight.

In order to construct flight itineraries the matrices focusing on network passenger volume and distance groups were used. However, for the sake of time, the Matlab code (provided in Appendix C) had to be structured for determining optimized flights in an effective manner.

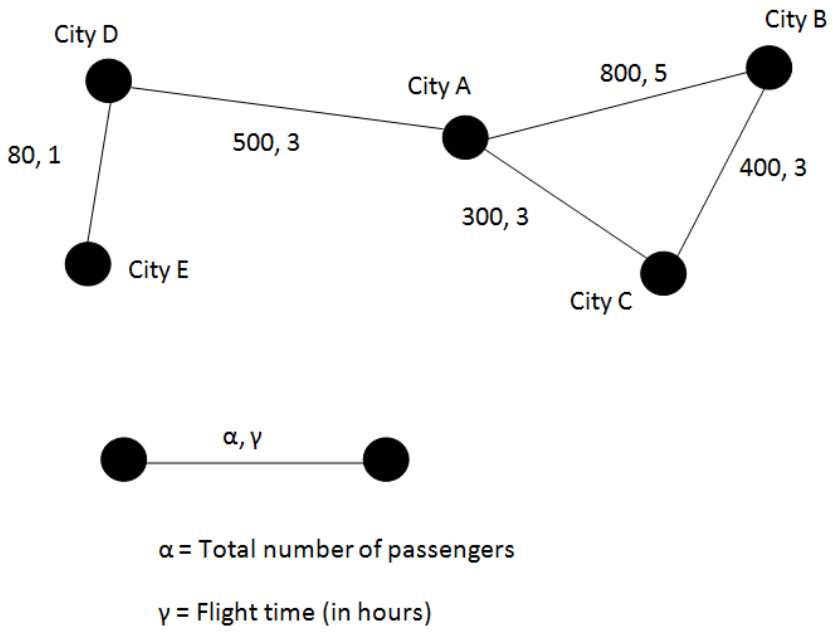

Figure 7. Second Example of an Airport Network

One method to find the optimal flight path is to generate every combination of flights possible. For example, using Figure 7, combinations such as A-B-C-D-E and A-B-C-E-D could be observed. However, since City E is only connected to City D, a flight path of A-B-C-E-D would not be possible. With the data from the U.S. Bureau of Transportation Statistics (2013), the model evaluates flight paths with 700 airports available. Therefore, in order to evaluate feasible flight paths efficiently, only feasible flights are generated. In the notional example above, if one started at City E, flight path E-D-A-B-C and E-D-A-C-B are evaluated. Since the sum of total passengers is 1780 using path E-D-A-B-C and 1280 using path E-D-A-C-B, the first path would be preferred in an attack starting from City E. In addition, terminating null airports exist so that an optimal flight itinerary using less than four flights can be selected.

If it is assumed that using the network in Figure 7, a terrorist has 10 hours to travel (not including layover time), he has two choices when launching an attack from City E. He can use flight path E-D-A-B or E-D-A-C-B based on a 10 hour time constraint. Since path E-D-A-B has a sum of 1380 total passengers and path E-D-A-C-B has a sum of 1280 total passengers, the first path is selected. Since the itinerary optimizing routine utilizes four flights, a fourth flight to a null terminating airport is used to fill the requirement without adding noise to the sum of the total number of passengers.

In order to score every feasible flight path efficiently, Figure 8 illustrates the method used.

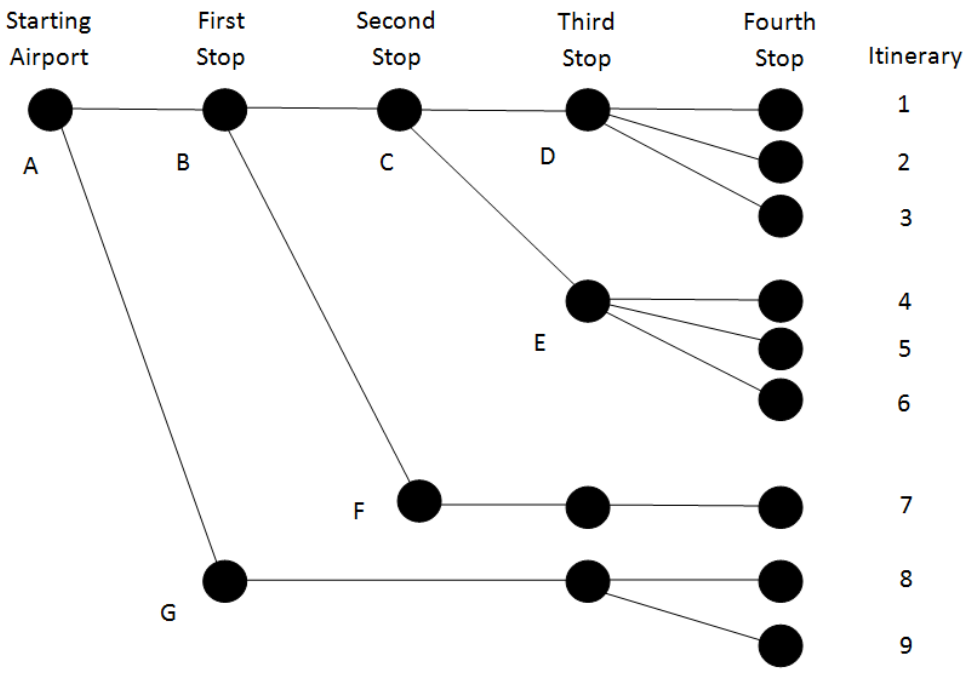

Figure 8. Visual Reference for Evaluating All Feasible Flights Efficiently

Based on the illustrative example, the itinerary optimizing program executes with the first airport code provided in the total passenger matrix (in this case, node A). Using this airport, an adjoining list of potential connecting flights would be generated, with the airports serving as a first stop (nodes B and G). Once this list was generated, the first airport serving as a first stop would be selected (node B) and another list of potential connecting flights would be generated (with these airports (nodes C and F) serving as a second stop). Similarly, the first airport serving as a second stop would be selected (node C) and another list of potential connecting flights would be generated (with these airports (nodes D and E) serving as the third stop). Finally, the first airport serving as the third stop would be selected (node D) and another list of potential connecting flights would be generated (with these airports serving as a final destination). The model then evaluates a

score based on the total volume of passenger traffic flowing from the starting point to the first stop, the first stop to the second stop, the second stop to the third stop, and the third stop to the fourth stop.

Referring again to Figure 8, itinerary 1 would be evaluated first. Next, the second airport on the fourth stop list would be evaluated (in this case, itinerary 2), and then the next one until all the fourth stop destinations were enumerated and evaluated. The program then looks at the first airport in the starting location (node A), the first airport in the first stop list (node B), the first airport in the second stop list (node C), the second airport in the third stop list (node E), and the first airport in the fourth stop list (in this case, itinerary 4). This continues until all possible airport itineraries starting from the first starting location (node A) were evaluated based on the total volume of traffic. Once the optimized itinerary (based on the total volume of passengers) has been found starting at the first airport, it is recorded. The program then proceeds to the second airport acting as a starting location and in a similar fashion evaluates all possible flight itineraries. Essentially, for each starting location, every combination of flight itineraries is evaluated and the path with the most traffic is recorded. With the inclusion of terminating null airports, a flight path with a large volume of traffic can be included if the path relies on less than four flights to real airports.

Constraints

In order to produce useful results, the itinerary optimizing routine limits the number of flights travelled. Ideally, a terrorist may want to infect as many people as possible before getting caught or succumbing to a disease. Therefore, instead of focusing

on one flight, multiple flights were considered. This included booking a maximum of four flights during the day. While most airlines try to get passengers from one airport to another in the least amount of flights, it is possible to go onto websites such as Kayak.com and Expedia.com and book itineraries that rely on more than two flights. This is especially noticeable with less costly routing, flights booked last minute (where common, shorter routes are fully booked), flights booked to airports with limited connections, and airlines that capitalize on various hubs.

As an illustrative example booking a flight on Kayak.com on 3 Feb 2014 with the itinerary presented in Figure 9:

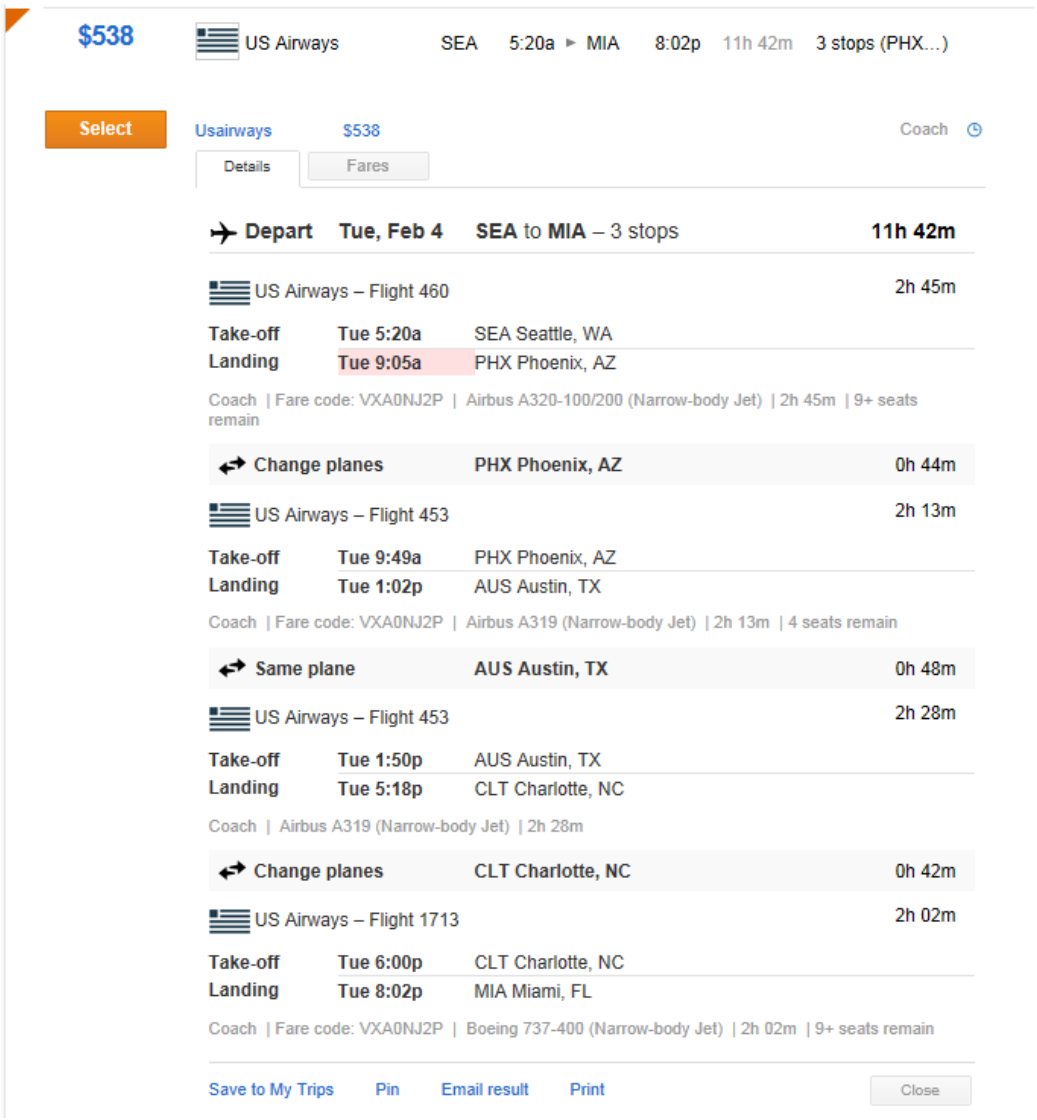

Figure 9. Four Flight Itinerary Example 1 (using Kayak.com) for Illustrative Purposes

The example clearly illustrates that if a terrorist were to purchase a ticket for the following day, they could book an itinerary with four flights within a 12 hour travel time. Specifically, the flight plan in Figure 9 would start with a trip from Seattle, WA to Phoenix, AZ, then fly from Phoenix, AZ to Austin, TX, followed by a flight leg from Austin, TX to Charlotte, NC, and concluding with a flight from Charlotte, NC to Miami,

FL. By relying on major hubs and the frequency of flights between these hubs, it is very likely that a terrorist cell could take advantage of flights such as these. Likewise, a similar route utilizing different hubs (due to different airlines) is possible as well;

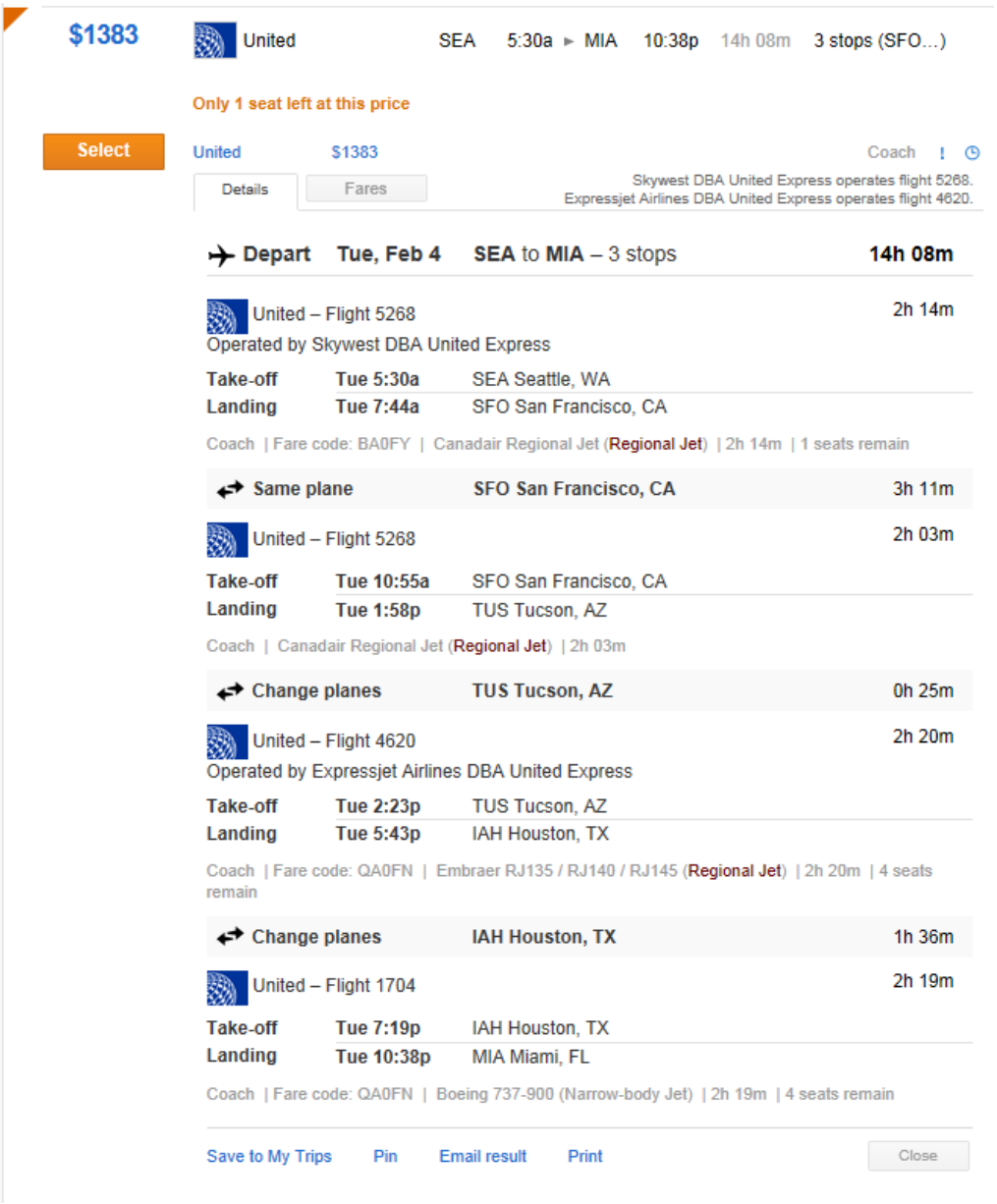

Figure 10. Four Flight Itinerary Example 2 (using Kayak.com) for Illustrative Purposes

In the example in Figure 10, the flight path would include a flight from Seattle, WA to San Francisco, CA, followed by a flight from San Francisco, CA to Tucson, a flight from AZ, Tucson, AZ to Houston, TX, and finally a flight from Houston, TX to Miami, FL. Due to the utilization of different airports by various airlines, network analysis was conducted on the U.S. air traffic network (regardless of airline) and on the networks of four large airlines.

Based on the examples shown, the model searches for the itinerary (of up to four flights) with the largest total volume of traffic (for December 2012) within an 18 hour window (corresponding to the constraint in Equation 3). This 18 hour window includes the flight time for all flights and an estimated one hour layover at each airport visited. The 18 hour window was selected due to many airports opening usually around 5-6AM and closing around 11PM -12AM. In addition, for a disease such as smallpox, the terrorist should be able to conduct their attack so long as they do not raise any suspicions from TSA or the public. Aside from the terrorist's behavior, physical symptoms such as pox could give them away. Therefore, assuming an infectious terrorist can survive a day of travel before showing signs or succumbing to the disease reinforces the idea of the 18 hour window selected. Although time zones would change the length of potential flight time (for example, someone flying from the east coast to the west coast would have a larger time window for flying within a day), for demonstration purposes the model does not account for time zone changes. This does not create a significant impact on the results generated by the model since a flight from west to east (such as a flight from Hawaii to California) could be done overnight on a redeye flight, allowing the 18 hour window to start at night and end during the day. If the flight itinerary is within the continental US, as

shown in Figure 9 and Figure 10, a flight itinerary from the west coast to the east coast can be done within an 18 hour travel day. Furthermore, the 18 hour window is with consideration to surviving a disease. Regardless what time of day it is, once the infectious period starts, a person carrying a disease is assumed by the model to have a least a window of a day to infect others before showing noticeable symptoms or succumbing to the infection.

Additional Considerations

While most of the focus was placed in the flight itinerary for a terrorist exposing the number of people within the entire airport network, several other factors were considered and evaluated. One area that is studied is the use of specific airlines. Referring back to Figure 9 and Figure 10, it is clear that both itineraries are offered by specific airlines. Specific airlines are likely to utilize certain hubs, which leads to different effective itineraries for each airline. In order to evaluate certain airlines, new matrices, using flights specifically serviced by an identified airline, were created and run through the flight itinerary selection code.

Another area that was studied was if known BioWatch locations are taken into consideration. Recall (Chapter 2) that the BioWatch program is currently implemented in 31 major cities, 11 of which have been publicly identified. In order to increase casualties and ensure a widespread infection, a terrorist may try to avoid cities with BioWatch. Therefore, analysis was conducted on flight itineraries that specifically avoid airports known to have BioWatch detection units. This was done by changing all values for distance groups going into or out of an airport on the BioWatch list to zero (essentially

disconnecting known BioWatch equipped airports from the rest of the airport network). It should be noted that if the goal of an attack was simply to shut down the air traffic system and spread panic, a terrorist could choose itineraries that focused on BioWatch cities. While this alternative was not modeled, it would be easy to adjust the model to consider it.

Finally, international arrivals are a concern due to their potential for a global wide exposure in a malicious attack. In addition, those travelling from abroad may unknowingly bring a disease into the U.S. that the U.S. public may not be prepared. To investigate this type of attack, it was assumed a malicious attack is launched from abroad and an infected terrorist can withstand two additional flights before succumbing to the biological agent, analysis was conducted utilizing a two flight itinerary. For this alternative approach, only the top 10 international US airports were considered. Again, it is clear that if intelligence about a specific anticipated attack were known, the scenario and analysis could be adjusted to investigate the attack.

Cascade Network

Another network structure, cascade networks, were utilized for determining key airports for detection. In this scenario, a disease starts in one location and is passed on to other locations. The goal of this strategy is to infect as many airports as possible quickly. The Matlab code used for this thesis is provided in Appendix C.

Cascade Network Set Up

In order to use a cascade network properly, a threshold must be specified for an airport to be considered infected. Therefore, the data used in this approach incorporates

the average number of passengers per flight (based on the December 2012 data from the U.S. Bureau of Transportation Statistics). Similar to the flight itinerary approach, matrices were constructed documenting the average number of passengers per flight travelling between two airports. The distance group matrix was also used as a proxy for time.

In order to track the airports in a cascade network, three states were identified: susceptible, infected, and compromised. Next, three matrices were formed based on those states. For the susceptible airports, let matrix *S* be an *n* x 2 matrix. In this matrix the first column lists the airport code and the second column denotes if the airport belongs to the respective matrix. For example, an airport that is still susceptible will have a one next to its code in the susceptible column, while a compromised or infected airport will have a zero in the second column of the susceptible matrix.

An infected matrix used to keep track of an airport that has been infected by at least a few passengers, but not enough to compromise the airport. For the infected state, let matrix *I* be an *n* x 4 matrix. The first two columns indicate the airport code and whether the airport belongs to this group (similar to the susceptible and compromise matrices). The third column is used to keep track of the number of infected passengers that have entered the airport and the fourth column is used to track the percentage of incoming traffic infected. Essentially, the infected matrix is used to track airports that are not compromised by the first infected flight, but eventually become compromised as additional infected flights are received by the airport.

For the compromised airports, let matrix *C* be an *n* x 3 matrix. Similar to the susceptible matrix, the first column contains each airport's code. The second column

(initially set to zero) marks the time an airport becomes compromised. The third column estimates the number of infected passengers arriving at the compromised airport. An airport is considered compromised if more than 100 passengers or more than 10% of the airport's total traffic reach a specified airport. The 100 passenger count is selected for illustrative purposes and is used for determining whether large airports are compromised. The 10% threshold is used for smaller airports in remote areas that do not experience large traffic volume. While these thresholds are notional in this illustration, these can be changed in the model to reflect an actual pathogen.

Cascade Execution

After the three matrices are set up, the cascade network model originating at the first airport and the clock starts. Any flights leaving this airport infect the connecting airports. Once enough time has passed for flights originating at the first airport to have landed and disembarked passengers, all connecting airports are removed from the susceptible matrix. If a connecting airport is compromised, it is moved from the susceptible matrix to the compromised matrix and any flights leaving that airport infect connecting airports. If a connecting airport is only infected, it is moved from the susceptible matrix to the infected matrix. As additional flights from other compromised airports land in the infected airport, the infected airport will eventually become compromised. This cycle repeats until a specified time limit has been reached. Actual rates can be adjusted to represent a specific pathogen used in an attack.

Once the cascade network has reached its specified time limit, the clock and matrices are reset. Another scenario will begin starting at the second airport on the list

until a specified time limit has been reached. Although this takes some time, the program will model a cascade network with every airport starting as a source for a disease spread.

To illustrate how the cascade network operates, consider the notional example using Figure 11 through Figure 15. In this notional example, it is assumed that all flights in this example take one hour to travel and 100 infected passengers are needed to compromise an airport. In Figure 11, the infection starts at City A.

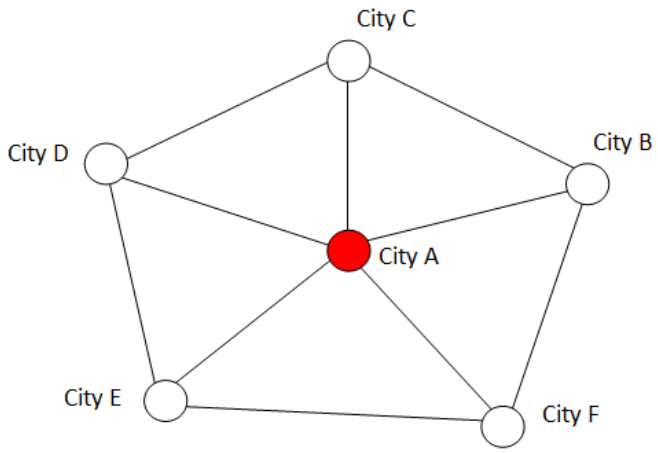

Figure 11. Cascade Example

During the first hour, all flights leave City A. Based on Figure 12 and the numbers used for this example, City B, D, and F are expected to be infected.

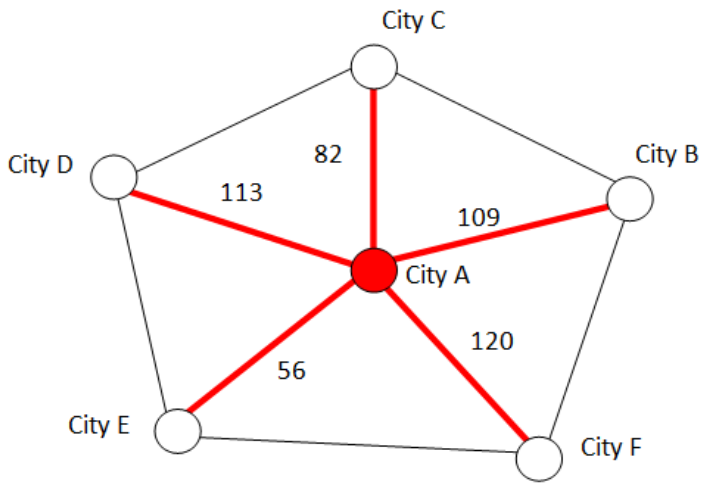

Figure 12. Cascade Example (During First Hour)

During the second hour, passengers disembark and City B, D, and F are compromised. Since City C and E did not have 100 or more passengers arrive from City A, they are only considered infected (as shown in Figure 13).

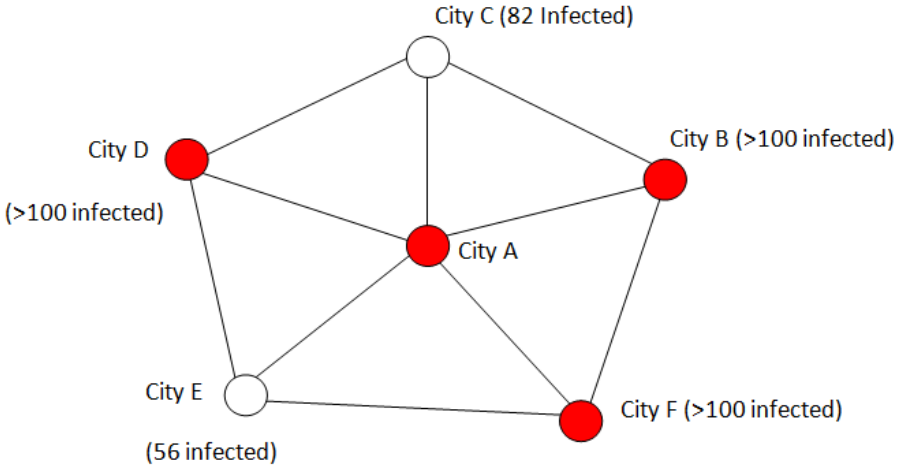

Figure 13. Cascade Example (During Second Hour)

After a one hour layover, additional flights take off during the third hour, as shown in Figure 14.

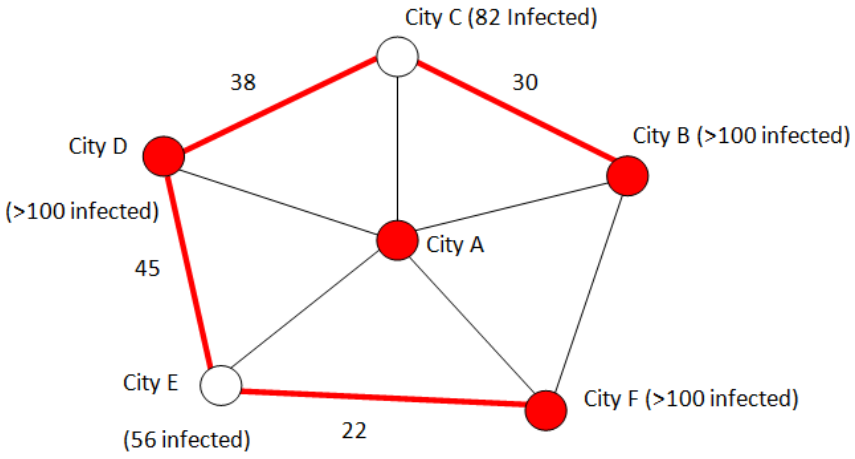

Figure 14. Cascade Example (During Third Hour)

Since City C and E have received more than 100 infected passengers by the fourth hour, they are considered compromised as shown in Figure 15.

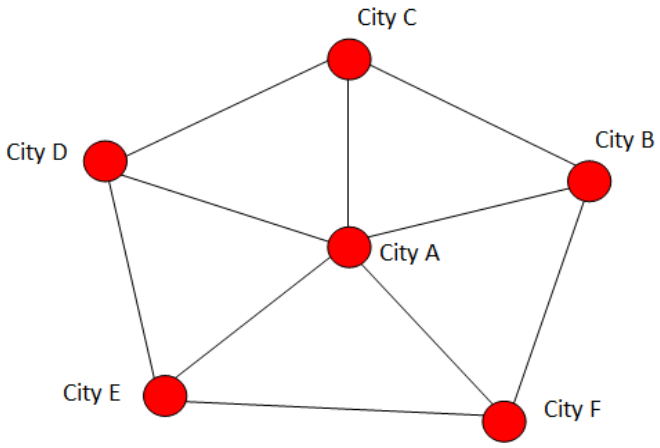

Figure 15. Cascade Example (During Fourth Hour)

The cascade network used in conjunction with the December 2012 data from the U.S. Bureau of Transportation Statistics operates in a similar method.

Measures

In order to measure which airports would be effective in creating itineraries for conducting a massive disease attack, at least one measure had to be used. While the model could have looked at the minimum amount of time needed to infect all airports or the maximum number of airports infected after a specified number of hours, these measures give equal weight to small and large airports. Therefore, the cities known to have the BioWatch program were used as indicators of a quick spread. Since these airports are considered critical in the network, it makes sense to stage an attack that can infect these airports in the shortest amount of time possible. Although this would mean the attack *may* be detected sooner, this is only possible if the BioWatch units are looking for less lethal diseases. In addition, a shorter time needed to infect critical airports probably means that the starting airport location has more connecting flights to major hubs than a remotely located airport. This could also mean the potential to infect more passengers and expose more damage on the airport network.

Although the network can identify which airports promote a shorter time needed to infect cities listed under the BioWatch program, a second discriminant is needed to evaluate these airports. The total number of infected passengers travelling from compromised airports are summed and recorded for each starting location. This means that the key starting airports can be differentiated with time acting as the first criteria and the infected passenger number as a discriminate (between starting airports with the same infection time).

Based on this model formulation, it is obvious that there is no consideration for multiple flight itineraries for infected passengers. In other words, if a passenger reaches

an airport that becomes infected but is not compromised, any susceptible airports that the infected passenger travels to will not be infected in the model. This is due to the way an airport infection is treated. In this instance, an airport must be compromised, or have enough of a pathogen travelling amongst passengers, that it is fair to consider all connecting airports infected. If only a few infected passengers reached an airport, the assumption that all connecting flights leaving the airport would infect their connecting airport would not be logical (unless we are dealing with a small airport and the percentage of traffic threshold is met). It is possible that the disease could be spread, but the trace amounts in an airport with only a few infected passengers would need to be modeled differently than in the demonstration. For example, if a very virulent infection were used, different tolerances other than (100/10%), could be used to model the compromise of an airport network.

Phase II

In this part of a notional attack, the concern is if a biological weapon is unleashed and the BioWatch system fails to detect an outbreak in time. The goal of this section is to examine an alternate policy to deal with the contagion. Using a disease spread model, it is possible to test the impacts of mass vaccination, trace vaccination, and pre-vaccination.

Kaplan et al. (2002) Model

In order to study the spread of a disease, the model by Kaplan *et al*. (2002) is used. As discussed in Chapter 2, this model is used to study the outcomes of a mass and trace vaccination program. As a result of reproducing this model, an alternative strategy to combat a smallpox outbreak was studied. By determining the spread of a disease over

time and using the estimated number of infected and casualties as measures, different containment policies can be analyzed.

In Kaplan *et al.*'s (2002) paper, the authors mention using exponential functions in their model. Although these functions were not provided, the rate of change for each state is given. Using the same starting conditions as the authors, the rate of change for each state of the model was calculated and added to the starting condition in incremental time periods. This allows the model to be discretized and successfully reproduce results of the Kaplan *et al*. (2002) model.

In addition, the model was parameterized in the thesis. This allows a user to change the parameters in order to model other diseases using the same Markov structure. Therefore, should one need to model a different disease outbreak (that can spread amongst humans), the impact can be predicted. Parameterizing the model also allowed for sensitivity analysis to be conducted. By changing various parameters such as the length of the infection and incubation periods, the outcomes of a more (or less) virulent outbreak can be studied. This is useful should a modified smallpox outbreak occur due to a mutation in the virus (the Matlab code used is provided in Appendix B).

Kaplan Model Reconstruction

As mentioned earlier, one model that has been used to study disease spread and containment is the Kaplan *et al*. (2002) model (referred to hereafter as the Kaplan model). It is structured as a continuous Markov chain with the layout presented in Figure 16. This section summarizes the Kaplan model and follows directly from the authors' article.

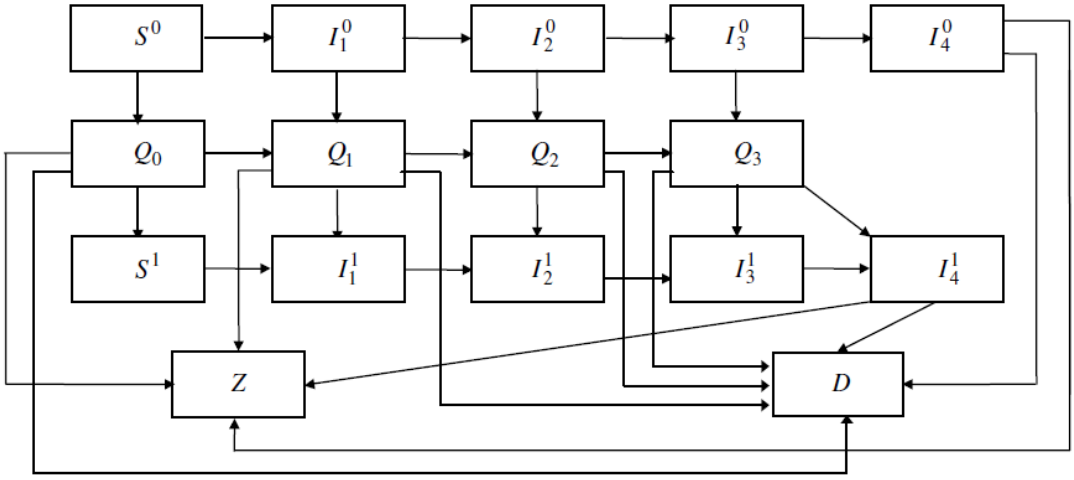

Figure 16. Kaplan Model Markov Chain

(Kaplan, Craft, & Wein, 2003, p. 6)

In this model, 'S' refers to those susceptible to the disease, 'Z' refers to those immune to the disease, and 'D' refers to those who die from smallpox. The 'I' and 'Q' stages refer to those with the disease and those in line for a vaccination, respectively. The subscript refers to which stage of the disease people fall under, while the superscript indicates if a person is vaccinated (using a one) or not (using a zero) (Kaplan *et al.*, 2002, p. 10939).

Kaplan's model starts with several parameters shown in Table 4.

Table 4. Kaplan's Variables for Smallpox Model

Parameter	Description	Value for smallpox
β	Infection rate	10^{-7} person^{-1} day^{-1}
c	Names generated per index	50
p	Fraction of infectees named by index	0.5
N	Population size	10^7
r_1	Disease stage 1 rate (asymptomatic, noninfectious, and vaccine-sensitive)	(3 days)$^{-1}$
r_2	Disease stage 2 rate (asymptomatic, noninfectious, and vaccine-insensitive)	(8 days)$^{-1}$
r_3	Disease stage 3 rate (asymptomatic and infectious)	(3 days)$^{-1}$
r_4	Disease stage 4 rate (symptomatic and isolated)	(12 days)$^{-1}$
n	Number of vaccinators	5000
μ	Service rate	50/day
h	Fraction febrile in stage 3	0.9
α	Quarantine rate	(5 days)$^{-1}$
v_0	Vaccine efficacy, stage 0	0.975
v_1	Vaccine efficacy, stage 1	0.975
δ	Smallpox death rate	0.3
f	Vaccination fatality rate	10^{-6}
$I_1^0(0)$	Initial number infected	10^3
τ	Delay	5 days

(Kaplan *et al.*, 2002, p. 10936)

The first parameter, β, is the infection rate. This is the portion of susceptible people infected by those in stage 3 of small pox. Next is the names generated per index, or the number of people an infected person has had contact with. The parameter 'p' is the portion of potentially infected people that are named, found, and vaccinated. 'N' refers to the population size and 'r_i' is rate one is in a disease stage *i* (which is found by dividing one over the average number of days in that stage). Although there are four stages, as noted in the chart, a person at stage three is infectious and does not show symptoms. The service rate, μ, refers to the number of vaccines provided in a day. For those vaccinated, a portion noted using 'h' are febrile and isolated for α^{-1} days. The vaccine efficacy rates

refer to the likelihood of the vaccine is able to protect a person from a future exposure to smallpox (provided the person is either susceptible to the disease or only in stage 1). The vaccination fatality rate refers to those who could die from the vaccine. The initial number infected is the number of people who start at stage 1 in the beginning of an outbreak and the delay is how long the disease is able to spread before it is identified and vaccines are issued. All parameters and values are provided by Kaplan *et al.* (2002) in their paper. Although he does offer a second service rate in the case for mass vaccination (200/day), that number was not be used in this study (Kaplan *et al.*, 2002, p. 10936).

Kaplan *et al*. (2002) provided the rates of change in their model. In the following equations the variables are: *I*, refers to the infected stage; *S*, refers to the population; and *Q*, refers to queuing stages. Furthermore, the superscript zero indicates someone who is untraced and not vaccinated, while the superscript one indicates someone who is traced and vaccinated. The subscripts refer to the disease stage for those infected and or in a queue (Kaplan *et al.*, 2002, p. 10939).

The first equation is the number of people who are infectious and thus able to spread the disease. This is found by summing all those in stage 3 of the disease, regardless if the person is vaccinated (Kaplan *et al.*, 2002, p. 10938).

$$I_3 = I_3^0 + Q_3 + I_3^1 \quad \textbf{(11)}$$

Next the untraced differential equations are provided. This is key to the beginning of the model where people are not being vaccinated until an outbreak is determined. In this case, one can see the number of susceptible people is negative and constantly declining based on the number of infected people. When one looks at the rates for the

additional stages of the disease, the primary factor that determines the rate of progression is the length of time in the specified stage. In addition, each stage has people "enter" from the previous stage and exit to the next stage (Kaplan *et al.*, 2002, p. 10939).

$$\frac{dS^0}{dt} = -\beta I_3 S^0 - [c - pR_0(t)]\frac{S^0}{N} r_3 I_3 \quad \textbf{(12)}$$

$$\frac{dI_1^0}{dt} = \beta I_3 S^0 - \left\{[c - pR_0(t)]\frac{I_1^0}{N} + p\lambda_1(t)\right\} r_3 I_3 - r_1 I_1^0 \quad \textbf{(13)}$$

$$\frac{dI_2^0}{dt} = r_1 I_1^0 - \left\{[c - pR_0(t)]\frac{I_2^0}{N} + p\lambda_2(t)\right\} r_3 I_3 - r_2 I_2^0 \quad \textbf{(14)}$$

$$\frac{dI_3^0}{dt} = r_2 I_2^0 - \left\{[c - pR_0(t)]\frac{I_3^0}{N} + p\lambda_3(t)\right\} r_3 I_3 - r_3 I_3^0 \quad \textbf{(15)}$$

$$\frac{dI_4^0}{dt} = r_3 I_3^0 - r_4 I_4^0 \quad \textbf{(16)}$$

In Equation 12, the number of people in the susceptible stage is always declining. This is due to the interaction of susceptible and infected people in the $-\beta I_3 S^0$ term. The $[c - pR_0(t)]\frac{S^0}{N} r_3 I_3$ term determines the number of names identified as infected by each person through the trace program. In Equation 13, those who were susceptible but made contact with an infected person move into the 1st stage of the disease. Those progressing to the second stage of the disease or the trace program are removed from the first stage state. Similarly, stage 2 and 3 of the disease are dealt with in Equation 14 and 15. Those entering the stage reflect an increase number of people in the disease stage, while those traced or progressing to the next phase leave the state. Finally, Equation 16 deals with the last stage of the disease (which inevitably leads to death) (Kaplan *et al.*, 2002, p. 10939).

Once a disease outbreak is detected, the queuing states are included. For these differential equations, one key piece is the number of people vaccinated. Once people are

vaccinated or they progress to the next stage of the disease, they leave the current queue they are in.

$$\frac{Q_0}{dt} = [c - pR_0(t)]\frac{S^0}{N}r_3 I_3 - \beta I_3 Q_0 - \mu Q_0 min(1, \frac{n}{Q}) \quad \textbf{(17)}$$

$$\frac{Q_1}{dt} = \beta I_3 Q_0 - \left\{[c - pR_0(t)]\frac{I_1^0}{N} + p\lambda_1(t)\right\} r_3 I_3 - \mu Q_1 min\left(1, \frac{n}{Q}\right) - r_1 Q_1 \quad \textbf{(18)}$$

$$\frac{Q_2}{dt} = r_1 Q_1 - \left\{[c - pR_0(t)]\frac{I_2^0}{N} + p\lambda_2(t)\right\} r_3 I_3 - \mu Q_2 min\left(1, \frac{n}{Q}\right) - r_2 Q_2 \quad \textbf{(19)}$$

$$\frac{Q_3}{dt} = r_2 Q_2 - \left\{[c - pR_0(t)]\frac{I_3^0}{N} + p\lambda_3(t)\right\} r_3 I_3 - \mu Q_3 min\left(1, \frac{n}{Q}\right) - r_3 Q_3 \quad \textbf{(20)}$$

In Equation 17, the initial queue is filled with people from the trace program. However, people in line who are infected (the $\beta I_3 Q_0$ term) and vaccinated people (the $\mu Q_0 min(1, \frac{n}{Q})$ term) leave the initial queue. The remaining queues progress similar to the disease stages. The first stage queue is increased by people who are infected while in the queue, but decreased by vaccinations or progression onto the next phase of the disease. The second and third stage queue proceed in a similar fashion (Kaplan *et al.*, 2002, p. 10939).

The quarantine state is used for those in stage 3 of the disease who are febrile and quarantined for 5 days.

$$\frac{dH}{dt} = (1 - f)h\mu Q_3 \min\left(1, \frac{n}{Q}\right) - r_3 H - \alpha H \quad \textbf{(21)}$$

For Equation 21, the term $(1 - f)h\mu Q_3 \min\left(1, \frac{n}{Q}\right)$ refers to the number of people who survive the vaccine but have fever-like symptoms (due to receiving the vaccine after

the disease has already spread). Those who have been in quarantine for five days or progressed to stage 4 are removed from the quarantine state (Kaplan *et al.*, 2002, p. 10939).

Once people have been vaccinated in the queue states, the next state is a traced state but unsuccessfully vaccinated. For those who were either susceptible or in stage 1 of the disease, this means that even with the vaccination, their body cannot build up a tolerance to the disease and they will move to the additional states. With regards to those in stages 2, 3, or 4 of the disease, the vaccine does not help. This means that unless a person is quarantined, these people can still spread the disease as it progresses (Kaplan *et al.*, 2002, p. 10939).

$$\frac{dS^1}{dt} = (1-f)(1-\nu_0)\mu Q_0 \min\left(1, \frac{n}{Q}\right) - \beta I_3 S^1 \quad \textbf{(22)}$$

$$\frac{dI_1^1}{dt} = \beta I_3 S^1 + (1-f)(1-\nu_1)\mu Q_1 \min\left(1, \frac{n}{Q}\right) - r_1 I_1^1 \quad \textbf{(23)}$$

$$\frac{dI_2^1}{dt} = r_1 I_1^1 + (1-f)\mu Q_2 \min\left(1, \frac{n}{Q}\right) - r_2 I_2^1 \quad \textbf{(24)}$$

$$\frac{dI_3^1}{dt} = r_2 I_2^1 + (1-f)(1-h)\mu Q_3 \min\left(1, \frac{n}{Q}\right) + \alpha H - r_3 I_3^1 \quad \textbf{(25)}$$

$$\frac{dI_4^1}{dt} = r_3 (I_3^1 + Q_3 + H) - r_4 I_4^1 \quad \textbf{(26)}$$

In Equation 22, the term $(1-f)(1-\nu_0)\mu Q_0 \min\left(1, \frac{n}{Q}\right)$ refers to the unsuccessful vaccination of a person. The term $\beta I_3 S^1$ refers to the possibility of being infected and progressing to stage 1 (due to the interaction of a susceptible person with a failed vaccination interacting with the infected population). In Equation 23, the first stage of the disease with a failed vaccination is populated by those who either receive a vaccine

when they were susceptible (the $\beta I_3 S^1$ term) or while they were in stage 1 of the disease (the $(1-f)(1-\nu_1)\mu Q_1 \min(1, \frac{n}{Q})$ term). Those progressing to the second stage leave the I_1^1 state. Equation 24 is increased by those entering stage 2 after receiving a vaccine outside the effective treatment window. It is also populated by those who receive a vaccine but were already in stage 2 (thus the vaccine is useless). Those progressing to stage 3 leave stage 2. In Equation 25, people who received ineffective vaccines while in a previous stage or stage 3 enter this state. Those surviving quarantine also enter this state, while those progressing to the next stage leave. Finally, Equation 26 deals with those in quarantine, previously failed vaccine stages, or progress from stage 3 who will eventually progress to stage 4 of the disease (Kaplan *et al.*, 2002, p. 10939).

For those who have successful vaccines, they go into the Immune/Recovered state (as shown in Equation 27). All others unfortunately will wind up in the death state (as shown in Equation 28).

$$\frac{dZ}{dt} = (1-f)(\nu_0 Q_0 + \nu_1 Q_1)\mu \min\left(1, \frac{n}{Q}\right) + (1-\delta) r_4 (I_4^0 + I_4^1) \quad \textbf{(27)}$$

$$\frac{dD}{dt} = f\mu Q min\left(1, \frac{n}{Q}\right) + \delta r_4 (I_4^0 + I_4^1) \quad \textbf{(28)}$$

Although *R* and κ do not refer to disease stages or states within the Markov chain, they are key factors that must be considered. *R* refers to the average number of infections per person. When *R* is greater than one, this essentially means a person is spreading a disease to more than one person and an epidemic can occur. κ is used to determine the rate people are traced (Kaplan *et al.*, 2002, p. 10939).

$$R_0(t) = \int_0^{t+\tau} e^{-r_3 x}\beta[S^0(t-x) + Q_0(t-x) + S^1(t-x)]dx \quad \textbf{(29)}$$

$$R_0(t) \approx \beta[S^0(t) + Q_0(t) + S^1(t)]/r_3 \quad \textbf{(30)}$$

$$\kappa(u) = \frac{[c - pR_0(u)]r_3 I_3(u)}{N} \quad \textbf{(31)}$$

λ is used to determine the number of untraced contacts who are infected. This number is determined by *q*, which is a conditional probability of contact depending on the stage of the disease (Kaplan *et al.*, 2002, p. 10940).

$$\lambda_j(t) = \int_0^{t+\tau} e^{-r_3 x}\beta S^0(t-x) e^{-\int_{t-x}^{t}\kappa(u)du} \times \Pr\{Contact\ in\ stage\ j\ at\ t | infected\ at\ t-x\}dx \quad \textbf{(32)}$$

$$\lambda_j(t) \approx q_j(t)\frac{\beta S^0(t)}{r_3 + \kappa(t)} \quad \textbf{(33)}$$

$$q_j(t) = \prod_{k=1}^{j-1}\frac{r_k}{r_k + r_3 + \kappa(t)} \times \frac{r_3 + \kappa(t)}{r_j + r_3 + \kappa(t)} \quad \textbf{(34)}$$

$$q_1(t) = \frac{r_3 + \kappa(t)}{r_1 + r_3 + \kappa(t)} \quad \textbf{(35)}$$

$$q_2(t) = \frac{r_1}{r_1 + r_3 + \kappa(t)} \times \frac{r_3 + \kappa(t)}{r_2 + r_3 + \kappa(t)} \quad \textbf{(36)}$$

$$q_3(t) = \frac{r_1}{r_1 + r_3 + \kappa(t)} \times \frac{r_2}{r_2 + r_3 + \kappa(t)} \times \frac{r_3 + \kappa(t)}{r_2 + r_3 + \kappa(t)} \quad \textbf{(37)}$$

Using these equations, Kaplan *et al*. (2002) were able to model mass and trace vaccination programs.

Extensions to Kaplan et al.'s (2002) Model

Using the Kaplan *et al*. (2002) model as a base, we were able to discretize time to account for days and code parameters for several variables instead of having hard coded values. Given the equations provided, an attempt was made to replicate the authors'

results to verify the model. In order to do this, the same parameters specified by the authors were used. The first extension includes change to how the model treats time. Since all the parameters involving time were in days in the model developed for this thesis, the number of people susceptible, exposed, and so forth to the smallpox virus were calculated to a half hour rate and added to the previous number (in order to mimic the continuous functions Kaplan *et al*. (2002) use).

To carry out this calculation, one change had to be made. In the Kaplan *et al*. (2002) the equations rely on continuous equations while the daily time interval involves a discrete approach. Kaplan *et al*.'s (2002) models rely on the following term in an exponential function:

$$\mu \min\left(1, \frac{n}{Q}\right)$$

Unfortunately, in a discrete model, this creates complications. To illustrate the point, if one person is in line for a vaccine and the above term is used, then *dQ/dt* is approximately -50 people/day. However, if we modify the term as follows:

$$\min\left(1, \frac{\mu n}{Q}\right)$$

then if one person is in line for a vaccine, then *dQ/dt* is approximately -1person/day.

Essentially, the term $\frac{\mu n}{Q}$ is incorporated when the number of people infected in line in a day exceeds the number of total vaccines administered in one day. When Q exceeds μn, the term $\frac{\mu n}{Q}$ is less than one and the number of people in line cannot all be vaccinated (thus carrying excess people into the next day's queue).

The second extension of the Kaplan *et al*. (2002) model includes parameters which could be adjusted in order to model other diseases. Diseases such as viral hemorrhagic fevers and plague could be modeled using this structure due to their ability to spread from person to person and the possibility of death. All parameters used in Kaplan *et al*.'s (2002) equations are established in the first section of code using Matlab (included in Appendix B). This allows modifications to be made increasing the ability to model uncertainties and conduct sensitivity analysis. Once necessary parameters and starting conditions are defined, the program can be executed to reflect the disease of interest.

As discussed in the literature review, diseases that rely on mosquitoes for dissemination, such as malaria, are not ideal for this approach. However, the equations could be modified by including differential equations that include the mosquito population, the infection rate of mosquitoes, and the rate infected mosquitoes infect humans.

Table 5. Parameters For Other Diseases Using Kaplan *et al*. (2002) Model

Disease	Type	Category	r1	r2	r3	r4	Vaccine Efficacy	Death Rate
Smallpox	Virus	A	3	8	3	12	0.975	0.3
Plague*	Bacteria	A	1	1	1	1	Unknown***	0.5
Ebola**	Virus	A	5	0	7	7	Unknown***	0.65
Marburg**	Virus	A	5	0	7	7	Unknown***	0.25
Lassa**	Virus	A	10	0	7	7	Unknown***	0.18

* numbers are reflective of pneumonic plague. If bubonic plaque was used, Kaplan's model would have to be modified since victims given antibiotics within 24 hours of showing symptoms could still recover (however, this form of plaque spreads via fleas, not humans)
** for Ebola and Marburg, the transmission rate would need to be severely reduced. While there are cases of human-human spread, it requires close contact
*** Vaccines are either in the investigational phase, have been discontinued, or have not been evaluated for ethical purposes (DHS, 2004) (Fong & Alibek, 2005)

Additional Notes:
-According to Fong, Junin, Machupo, Guanarito, and Sabia virus could be modeled (same family and genus as Lassa virus), as well as Crimean-Congo Hemorrhagic Fever virus and the Andes virus (2005).
-If we consider diseases not recognized as biological agents, influenza, tuberculosis, and measles could also be modeled.
-All numbers reported in the table are averages, not ranges.

Kaplan et al.'s (2002) Use of Their Model

The model developed by Kaplan *et al*. (2002) was utilized to compare and contrast a mass vaccination and trace vaccination policy. By comparing the amount of time needed to contain an outbreak, the estimated number infected, and the estimated number of casualties between the two policies, the authors are able to show that a mass

vaccination policy is more effective in containing an outbreak. With a mass vaccination policy, the estimated number of casualties decreases by approximately 109,000 and the number infected decreases by approximately 365,000 (Kaplan *et al.*, 2002). With the pre-vaccination program, the results are not nearly as effective as a mass vaccination program. However, the pre-vaccination policy could be an effective alternative to trace vaccination.

Conclusion

Using the Bureau of Transportation Statistics, an airport network was constructed. With this network, variations such as a four flight itinerary, flight plans based on several airlines, and a two flight itinerary from an international arrival hub are alternative methods for determining airports with significant passenger traffic. By using a cascade network approach, key airports for disease propagation are able to be recognized. As displayed in Figure 4, analysis of these itineraries identify key airports that need to be protected with biodetection equipment. In addition to the network approaches, Kaplan's model was extended. In the event of a disease outbreak, appropriate measures can be taken to mitigate the effects. The Results and Analysis chapter, which follows, present the outcomes of the network analysis and disease spread models, as well as help identify key measures that should be implemented.

4. Results and Analysis

Introduction

The Results and Analysis chapter highlights key findings from an analysis of a case scenario with the models built. Once the data was reorganized into matrices and the networks were generated, flight itineraries ideal for an attack were generated and identified. These flight itineraries focus on key flights in the network based on the passenger traffic volume travelling between airports. Aside from looking at the US airport network as a whole, analysis was conducted with respect to several airlines, BioWatch considerations, and international arrivals. Cascade networks were also applied as in the notional example.

Kaplan's model, extended for this study, was also applied in the notional scenario. The primary focus of analyzing the Kaplan *et al.* (2002) model was to observe an alternate strategy for mitigating an outbreak. In addition, several factors were changed for additional insight, especially with regards to bio-engineering. Using these results, key policies and strategies can be recommended for combating various biological threat scenarios.

Airport Network (up to Four Flight Itinerary)

The first scenario run involved generating four flight itineraries. Before looking at the itineraries, it is worth reviewing the top ten flights based on the volume of passengers. This data is based on the flight data from the U.S. Bureau of Transportation Statistics for December 2012. These are presented in Table 6.

Table 6. Top Ten Directed Flights

Origin	Destination	Passengers
San Francisco	Los Angeles	139,889
NY (JFK)	Los Angeles	132,190
Los Angeles	NY (JFK)	130,561
Los Angeles	San Francisco	128,409
Atlanta	Orlando	112,906
NY (LGA)	Atlanta	104,653
Atlanta	Fort Lauderdale	104,375
Chicago	NY (LGA)	103,258
Atlanta	NY (LGA)	102,863
Orlando	Atlanta	102,639

If the direction of the flight was not important, the most frequently travelled flights are as presented in Table 7.

Table 7. Top Ten Undirected Flights

Airport Pair		Passengers
San Francisco	Los Angeles	268,298
NY (JFK)	Los Angeles	262,751
Atlanta	Orlando	215,545
NY (LGA)	Atlanta	207,516
Chicago	NY (LGA)	204,304
Fort Lauderdale	Atlanta	197,836
Los Angeles	Chicago	180,277
Los Angeles	Honolulu	177,743
Dallas	Los Angeles	176,985
Honolulu	Kahului	174,166

In reviewing these flights, a few items should be noted. First, most of the highly populated routes include cities where BioWatch is known to have been implemented. While there are a few cities not specifically mentioned as part of the program that are in these top ten lists, cities such as New York, Atlanta, Los Angeles, and San Francisco are obvious choices for the program. There are a few interesting airports listed, however. The

ones that stand out are those to or from Florida. Cities such as Fort Lauderdale and Orlando are not nearly as populous as New York. However, due to tourism and vacationing, especially for a cruise, these airports are frequently used. Kahului, HI is included for similar reasons as well. One other noticeable trend is the high volume of traffic between San Francisco and Los Angeles. This is surprising due to their relatively close location, which will affect the itinerary optimizing routine. Due to an optimization based on passenger traffic, flight itineraries going from the east coast to the west coast (or vice versa) include this connection based on its extremely large volume (see Table 8).

Initially, no distance constraints were included in the model (however, the network was programmed not to include a cycle of airports). The results displayed in Table 8 were generated by finding an optimal flight itinerary based on traffic starting at every airport. These results were then ranked based on their score, which is the sum of all traffic for each flight pair incorporated in the itinerary in a month.

Table 8. Top Ten Flight Itineraries (without distance constraints)

	1	2	3	4	5	Score
1	New York City, NY (LaGuardia)	Chicago, IL (O'Hare)	San Francisco, CA	Los Angeles, CA	New York City, NY (JFK)	448,005
2	New York City, NY (JFK)	Los Angeles, CA	San Francisco, CA	Chicago, IL (O'Hare)	New York City, NY (LaGuardia)	442,724
3	San Francisco, CA	Los Angeles, CA	Chicago, IL (O'Hare)	New York City, NY (LaGuardia)	Atlanta, GA	437,974
4	Atlanta, GA	Orlando, FL	New York City, NY (JFK)	Los Angeles, CA	San Francisco, CA	428,707
5	Phoenix, AZ	Denver, CO	San Francisco, CA	Los Angeles, CA	New York City, NY (JFK)	423,653
6	Las Vegas, NV	Denver, CO	San Francisco, CA	Los Angeles, CA	New York City, NY (JFK)	417,135
7	Orlando, FL	Atlanta, GA	San Francisco, CA	Los Angeles, CA	New York City, NY (JFK)	417,004
8	Chicago, IL (O'Hare)	New York City, NY (LaGuardia)	Atlanta, GA	Los Angeles, CA	New York City, NY (JFK)	416,120
9	Dallas, TX (DFW)	Chicago, IL (O'Hare)	San Francisco, CA	Los Angeles, CA	New York City, NY (JFK)	415,693
10	Los Angeles, CA	San Francisco, CA	Chicago, IL (O'Hare)	New York City, NY (LaGuardia)	Atlanta, GA	415,187

Based on these results, the need for distance constraints was obvious. Clearly, the first result involves as close to a complete round trip (without using the same airport twice) as one will get. This result would not make sense due to the approximately twenty minute drive needed to get from LaGuardia to JFK International Airport (or the needless visit to the west coast only to get back to the east coast in the same day). Other results, such as itinerary 7, involve an unnecessary and unrealistic flight path to get from Orlando to New York.

After observing the distance groups between airports in the results displayed in Table 6, distance constraints were programmed into the model. The following results were generated:

Table 9. Top Ten Flight Itineraries (with Los Angeles & San Francisco connection)

	1	2	3	4	5	Score
1	San Francisco, CA	Los Angeles, CA	Dallas, TX (DFW)	Atlanta, GA	New York City, NY (LaGuardia)	398,936
2	New York City, NY (Laguardia)	Atlanta, GA	Dallas, TX (DFW)	Los Angeles, CA	San Francisco, CA	391,878
3	Honolulu, HI	San Francisco, CA	Los Angeles, CA	Chicago, IL (O'Hare)	New York City, NY (LaGuardia)	368,777
4	Santa Ana, CA	San Francisco, CA	Los Angeles, CA	New York City, NY (JFK)	San Juan, PR	363,903
5	Tampa, FL	Atlanta, GA	Dallas, TX (DFW)	Los Angeles, CA	San Francisco, CA	363,374
6	New York City, NY (JFK)	Los Angeles, CA	San Francisco, CA	Honolulu, HI	Kona, HI	361,583
7	Kona, HI	Honolulu, HI	San Francisco, CA	Los Angeles, CA	New York City, NY (JFK)	360,469
8	Lihue, HI	Honolulu, HI	San Francisco, CA	Los Angeles, CA	New York City, NY (JFK)	357,122
9	Orlando, FL	Atlanta, GA	Dallas, TX (DFW)	Los Angeles, CA	Honolulu, HI	353,311
10	Oakland, CA	Los Angeles, CA	San Francisco, CA	Chicago, IL (O'Hare)	New York City, NY (LaGuardia)	349,086

Clearly, the itineraries appear more realistic (and less like a erratic cross country trip). However, every path in the top ten results used the connection between Los Angeles and San Francisco. While it is not unreasonable to use this flight to connect to other

flights, most online travel websites will use *either* San Francisco or Los Angeles to get from Hawaii to the east coast (not both).

In order to make the network more realistic (in terms of booking flights), the flight linking Los Angeles and San Francisco was cut (the volume of traffic between the two airports is changed to zero so the program does not consider the flight as part of an optimal path). With this network, the following top flights were generated:

Table 10. Top Ten Flight Itineraries

	1	2	3	4	5	Score
1	New York City, NY (LaGuardia)	Atlanta, GA	Dallas, TX (DFW)	Los Angeles, CA	Honolulu, HI	355,325
2	Honolulu, HI	Los Angeles, CA	Dallas, TX (DFW)	Atlanta, GA	Orlando, FL	354,977
3	Orlando, FL	Atlanta, GA	Dallas, TX (DFW)	Los Angeles, CA	Honolulu, HI	353,311
4	San Francisco, CA	Las Vegas, NV	Los Angeles, CA	New York City, NY (JFK)	San Juan, PR	341,263
5	Boston, MA	New York City, NY (JFK)	Los Angeles, CA	Honolulu, HI	Kona, HI	333,189
6	San Juan, PR	New York City, NY (JFK)	Los Angeles, CA	Las Vegas, NV	San Francisco, CA	332,382
7	Lihue, HI	Honolulu, HI	Los Angeles, CA	Chicago, IL (O'Hare)	New York City, NY (LaGuardia)	330,535
8	Kona, HI	Honolulu, HI	Los Angeles, CA	Atlanta, GA	Orlando, FL	329,199
9	Tampa, FL	Atlanta, GA	Dallas, TX (DFW)	Los Angeles, CA	Honolulu, HI	326,821
10	Fort Lauderdale, FL	Atlanta, GA	Los Angeles, CA	Honolulu, HI	Kona, HI	323,948

Based on the itineraries presented in Table 10, it is clear that the program can generate reasonable flight itineraries. While there might be a slight discrepancy, such as in itinerary number 4 with the first three flights, overall the results look like actual options on an online travel site. If one wanted to manually switch one of the flights, it could be done, but the itinerary will no longer be optimized. It should also be noted that itinerary 2 and 3 are the same, but involve starting in different locations.

Clearly, the itineraries utilize a number of flights mentioned in the top ten most trafficked flights. In addition, every itinerary goes to at least two cities known to have

BioWatch. Although the score does not give us an estimate for the number of people affected on each itinerary, it highlights the volume of traffic using these flights (just during one month). Should an attack occur on one of these itineraries and just the flights mentioned were quarantined, the mass disruption in traffic based on these numbers could be devastating. An even greater impact would occur if the airports were closed or if people completely distrusted the airlines. In addition, while not included in the example, the dispersion of fliers who may have been infected throughout the nation could cause greater difficulties. If specific flight volume were available (perhaps right after an attack and its agent were detected) the true number of persons on those specific flights could be used. This would give a rough estimate of the number exposed.

Aside from attacking highly trafficked routes, detection could be considered while booking a flight itinerary. Therefore, the following cities might be avoided due to BioWatch; Philadelphia, New York, Washington DC, Boston, Chicago, San Francisco, Atlanta, St. Louis, Houston, Los Angeles, and San Diego. There are 21 additional cities that are reported to have BioWatch but have not been announced to the public. Assuming a terrorist organization wished to avoid detection in order to inflict mass infections, the following routes would be most beneficial:

Table 11. Top Ten Flight Itineraries (with BioWatch)

	1	2	3	4	5	Score
1	Anchorage, AK	Seattle, WA	Denver, CO	Dallas, TX (DFW)	Orlando, FL	233,541
2	Orlando, FL	Dallas, TX (DFW)	Denver, CO	Seattle, WA	Anchorage, AK	224,876
3	San Juan, PR	Orlando, FL	Dallas, TX (DFW)	Denver, CO	Las Vegas, NV	223,971
4	Las Vegas, NV	Denver, CO	Dallas, TX (DFW)	Orlando, FL	San Juan, PR	223,824
5	Burbank, CA	Las Vegas, NV	Denver, CO	Dallas, TX (DFW)	Orlando, FL	221,504
6	Austin, TX	Dallas, TX (DFW)	Phoenix, AZ	Honolulu, HI	Kahului, HI	220,245
7	Oakland, CA	Las Vegas, NV	Denver, CO	Dallas, TX (DFW)	Orlando, FL	218,634
8	San Antonio, TX	Dallas, TX (DFW)	Phoenix, AZ	Honolulu, HI	Kahului, HI	216,648
9	Charlotte, NC	Dallas, TX (DFW)	Phoenix, AZ	Honolulu, HI	Kahului, HI	215,756
10	Seattle, WA	Denver, CO	Dallas, TX (DFW)	Orlando, FL	San Juan, PR	213,294

Based on the results, there are obviously a number of cities that are vulnerable to an attack. Clearly, cities such as Dallas, Honolulu, Orlando, and Denver should be included in the BioWatch program, if they are not already. While disruption of these airports may not displace as much traffic as the itineraries generated using the whole network, the results are still critical. Just by initiating an attack from Seattle, WA (using itinerary 10 in Table 11), the estimated traffic volume during the month of December is still greater than 200,000 people. While only those on the actual flight on the day of the attack risk infection, based on volume, this is a potentially significant attack.

After considering BioWatch implications on the whole airport network, several airlines were analyzed. This was done to emulate most online travel websites which try to have users stay with one airline (as shown in Figure 9 and Figure 10). This saves the user money and makes it easier for airports to organize their terminals. Several airlines were selected and given names A, B, C, and D. These airlines were analyzed based on their

whole network and if a terrorist group was avoiding known detection sites (similar to the analysis just conducted with the whole airport network).

Based on the results using airline A, Dallas, TX was incorporated in every flight itinerary, regardless of BioWatch considerations. Once known BioWatch was included, San Juan, PR, Orlando, FL, and Miami, FL also appeared in every route. While these itineraries have very little variation, it is obvious that these airports would be critical nodes to compromise in terms of finance and traffic for the airline. The results are displayed in Table 30 and Table 31 in Appendix D.

Based on the network using airline B, similar results occurred. While Dallas, TX showed up in several routes, Phoenix, AZ and Charlotte, NC were included in every flight itinerary regardless if known BioWatch was considered or not. If known BioWatch cities were considered, Dallas appeared more frequently in the itineraries, along with Orlando. The results are displayed in Table 32and Table 33 in Appendix D.

Unfortunately, analysis of airline C produced some complications. While the San Francisco/Los Angeles connection was severed in the whole network analysis, it was restored in the airline analysis. It was assumed that by breaking the network up by airlines, no one airline would heavily rely on this specific flight. Unfortunately, airline C has a great deal of reliance on the San Francisco/Los Angeles connection if BioWatch is ignored. To make matters worse, when BioWatch was considered, no specific airport was used in a majority of the itineraries. While the flights were sporadic, there were a few airports that appeared several times. This included Honolulu, Orlando, Anchorage, Seattle, Denver, and West Palm Beach. Surprisingly though, Newark became a critical airport once known BioWatch was avoided. Based on the results of airline C, the San

Francisco/Los Angeles connection is vital to their network, while a few airports not known to have BioWatch may be important. The results are displayed in Table 34 and Table 35 in Appendix D.

Lastly, airline D was analyzed. When known BioWatch was not considered, Orlando was used in all itineraries. However, once known BioWatch was considered, Orlando was still popular, but it was not used in every itinerary. Instead, Seattle, Minneapolis, and Detroit were frequently used. Based on the results, airline D clearly relied on Orlando and its connection to New York and Atlanta. The results are displayed in Table 36 and Table 37 in Appendix D.

Two Flight with International Arrival Analysis

After considering the four flight itineraries within the country, international arrival flights were considered. Based on the Bureau for Transportation Statistics, the top ten airports that serviced domestic and international flights in 2012 were the following:

Table 12. Top Ten Airports for International Flights

Airport	Enplaned Passengers
New York City, NY (JFK)	12,334,200
Miami, FL	9,314,500
Los Angeles, CA	8,273,400
Newark, NJ	5,577,100
Chicago, IL (O'Hare)	5,055,200
Atlanta, GA	4,775,500
San Francisco, CA	4,534,800
Houston (Bush)	4,220,500
Washington, DC (Dulles)	3,205,100
Dallas, TX	2,885,100

Using a similar approach to the four flight itinerary, a two flight itinerary starting from each of these airports were generated. As shown in Table 38 in Appendix E, there was a large reliance on the using the San Francisco/Los Angeles connection. As done with the four flight itinerary for the whole network, this connection was severed. The model was executed again and the results are presented in Table 39 in Appendix E. By looking at the results, it is clear that most of the traffic flows to other large airports, most with BioWatch units.

Although most of the airports in Table 12 are known to have BioWatch, there are three exceptions; Miami, Newark, and Dallas. With BioWatch taken into consideration and the three named airports serving as ideal entry points from international flights, the following itineraries were generated:

Table 13. Top Ten using International Airports and Two Flights (Using BioWatch)

Start at Miami

	1	2	Score
1	Dallas, TX	Denver, CO	116,051
2	Dallas, TX	Phoenix, AZ	99,293
3	Dallas, TX	Las Vegas, NV	97,390
4	Orlando, FL	Newark, NJ	95,404
5	Dallas, TX	San Antonio, TX	94,106
6	Dallas, TX	Austin, TX	93,938
7	Denver, CO	Las Vegas, NV	89,678
8	Orlando, FL	Detroit, MI	86,305
9	Dallas, TX	Seattle, WA	83,385
10	Orlando, FL	Dallas, TX	81,561

Start at Newark

	1	2	Score
1	Denver, CO	Phoenix, AZ	111,480
2	Denver, CO	Las Vegas, NV	108,818
3	Dallas, TX	Denver, CO	100,055
4	Honolulu, HI	Kahului, HI	97,339
5	Orlando, FL	Miami, FL	96,327
6	Orlando, FL	Dallas, TX	95,201
7	Phoenix, AZ	Las Vegas, NV	94,472
8	Orlando, FL	San Juan, PR	93,589
9	Charlotte, NC	Dallas, TX	93,361
10	Orlando, FL	Charlotte, NC	91,640

Start at Dallas

	1	2	Score
1	Denver, CO	Las Vegas, NV	148,193
2	Denver, CO	Seattle, WA	134,158
3	Denver, CO	Salt Lake City, UT	129,683
4	Phoenix, AZ	Las Vegas, NV	116,033
5	Denver, CO	Portland, OR	113,820
6	Phoenix, AZ	Seattle, WA	108,747
7	Denver, CO	Santa Ana, CA	108,722
8	Honolulu, HI	Kahului, HI	103,071
9	Denver, CO	Sacramento, CA	101,031
10	Denver, CO	Omaha, NE	99,316

Based on the results in Table 13, it is clear that Denver, CO; Dallas, TX; Las Vegas, NV; and Orlando, FL are frequently visited. In addition, while the monthly volume of traffic is less than it was for the four flight itineraries, there is still roughly 100,000 people using these flights in a month (again, the values are monthly proxies for average traffic, not the actual number of passengers on the specific flights). Should a malicious attack from abroad be anticipated, these airports should be equipped with

BioWatch, if they are not already. If they are equipped, a review of inspection frequencies and protocols may be called for.

Cascade Network

Aside from building flight itineraries, a cascade network was also used to determine key locations to start a mass infection using the same information from the Bureau of Transportation Statistics based on the monthly traffic proxy. In this cascade network model, it is assumed that once a passenger threshold is reach, all flights leaving the compromised airport are infected. The expected number infected is the sum of people on flights leaving all the infected airports at the specified time (using the average number of people travelling per flight from the data). The minimum hour is the amount of time needed to reach all cities equipped with BioWatch (including one hour layovers). While these assumptions may not be realistic, they help distinguish key airports for initiating a disease outbreak and allow a consistent metric to help differentiate various starting locations. Using a threshold of either 10% volume of traffic or 100 infected passengers, while focusing on time and number infected, Table 14 summarizes the top ten results.

Table 14. Top Ten Starting Locations for a Cascade Network Infection (100 Person or 10% Threshold)

Minimum Hour	Expected Number Infected	Origin City
6	47,772	Dallas, TX (DFW)
6	45,943	Kansas City, MO
6	44,165	Denver, CO
6	31,187	Chicago, IL (Midway)
7	71,322	Minneapolis, MN
7	66,265	Sioux Falls, SD
7	65,338	Houston, TX (IAH)
7	63,992	Lincoln, NE
7	63,092	Indianapolis, IN
7	60,159	New Orleans, LA

Clearly, each of the cities listed in Table 14 is well connected and can reach all known airports with BioWatch within seven hours (assuming no delays, one hour layovers, and flights on the hour). It should be noted that all of the listed cities are located within the center region of the country (under the Central and Mountain Time Zones). By launching an attack from a central location, it makes sense that these airports would be well situated in a cascade scenario. While it is surprising that a city such as Kansas City, MO scored better than Houston, TX in the amount of time needed to reach all known BioWatch cities, Houston infected more people.

Another interesting observation is the reliance on Sioux Falls for a cascade spread. Although it infected the known BioWatch Airports in the same amount of time as Houston, TX and New Orleans, LA, it scored higher under the expected number infected. While airports such as Sioux Falls, SD; Lincoln, NE; and Kansas City, MO have not appeared nearly as frequently as Denver, CO or Dallas, TX throughout the flight itinerary analysis, it is clear that their location could still be exploited. If these cities are infected,

passengers from these cities are likely to connect to a high volume hub city in one flight. From there, the infection can cascade to other hubs and regional airports.

If the threshold is increase to 200 infected people or 20% of the traffic, Table 15 shows which airports serve as key starting locations (once again assuming no delays, one hour layovers, and flights on the hour).

Table 15. Top Ten Starting Locations for a Cascade Network Infection (200 Person or 20% Threshold)

Minimum Hour	Expected Number Infected	Origin City
7	96,713	Denver, CO
7	94,193	Dallas, TX
7	55,806	Lincoln, NE
8	113,948	Kansas City, MO
8	111,573	Wichita, KS
8	110,926	Atlanta, GA
8	106,190	Chicago, IL (Midway)
8	103,323	Baton Rouge, LA
8	102,387	Sioux Falls, SD
8	101,727	Monroe, LA

Clearly, Denver, CO; Dallas, TX; and Lincoln, NE still serve as prime areas to launch an attack. There are a few noticeable trends. As expected, with a higher threshold, the attack should take longer and involve more infections. It is interesting that the shortest amount of time only increased by an hour, while the number exposed increased by approximately 49,000. One other noticeable feature is the reliance on centrally located airports. While Atlanta is the exception, all other airports still fall in areas within the Central and Mountain Time Zone. Based on these results, should an attack occur in the

central portion of the country, an infection could spread to both coasts quickly. Similar to the lower threshold, airports located in the center of the country could easily be exploited.

Analysis for BioWatch Considerations

After analyzing various airlines and flight itineraries, the following cities should include the Biowatch program if they are not already involved:

Table 16. Suggested Airports for the BioWatch Program

Airport Network	Two Flight Scenario	Cascade
Orlando, FL	Newark, NJ	Dallas, TX (DFW)
Dallas, TX	Miami, FL	Kansas City, MO
Honolulu, HI	Dallas, TX	Denver, CO
Phoenix, AZ	Denver, CO	Minneapolis, MN
Charlotte, NC	Orlando, FL	Sioux Falls, SD
San Juan, PR	Las Vegas, NV	Lincoln, NE
Seattle, WA	Honolulu, HI	Indianapolis, IN
Miami, FL	Fort Lauderdale, FL	New Orleans, LA
Denver, CO		Wichita, KS
Newark, NJ		Baton Rouge, LA
Las Vegas, NV		
Minneapolis, MN		
Kahului, HI		
Detroit, MI		

Those recommended under the Airport Network results appeared in at least ten itineraries on the various airlines studied (results summarized in Table 40 in Appendix F). For the Two Flight Scenario results indicate which airports receive majority of the traffic from large international airports. The first three results are airports in the top ten two flight airport list but are not known to have BioWatch. The following results are airports that are frequently travelled to or from an airport hub that is known for receiving

international flights (summarized in Table 41 in Appendix F). Finally from the Cascade Network, several cities are ideal starting points to launch a biological attack, especially one involving a highly infectious disease with a short incubation period. Again, even if these cities do have BioWatch, a review of the inspection frequencies and protocols would be called for, particularly if intelligence supported such as attack.

These cities, such as Denver and Dallas, serve as major hubs and could be exploited if a terrorist group was trying to inflict damage while avoiding known BioWatch cities. Although Orlando and San Juan may appear to be random airports or a result of the program and its distancing constraints, there is a concern with regards to cruise lines and theme parks. With Orlando, the area is ideal for family vacations. With regards to San Juan and Fort Lauderdale, they serve as ideal locations for cruise lines to operate.

To illustrate how critical these airports are, consider the following itinerary (first result from the top ten itineraries with BioWatch considered):

Anchorage, AK → Seattle, WA → Denver, CO → Dallas, TX → Orlando, FL

If an attack occurred on this flight path, assuming the entire plane was compromised and half the passengers stopped flying after one flight, the following infections would occur (using the average number of passengers from the data):

-Approximately 146 infected passengers would arrive in Seattle, WA from Anchorage, AK, with 73 remaining there and a portion of passengers possibly going to Albuquerque, NM

-Approximately 138 infected passengers would arrive in Denver, CO from Seattle, WA, with 69 remaining there and a portion of passengers possibly going to Albany, NY

-Approximately 102 infected passengers would arrive in Dallas, TX from Denver, CO, with 52 remaining there and a portion of passengers possibly going to Atlanta, GA

-Approximately 134 infected passengers would arrive in Orlando, FL from Dallas, TX, with 67 remaining there and a portion of passengers possibly going to Scranton, PA

In this example, there could be an initial estimate of 520 passengers infected and 9 airports impacted.

While the assumption that a whole flight was infected may be unlikely, one can see that even if a few people are infected and spread out just to one additional location (other than where the terrorist is headed), the results are concerning. By just assuming passengers either get off at their arrival airport or head to only one other airport, a disease outbreak could occur in nine cities. In a real world scenario using this flight itinerary, the number of infected passengers heading to Albany, Albuquerque, Scranton, and Atlanta would probably be low. Unfortunately, the number of cities where the disease would spread could easily triple (assuming half the passengers had connecting flights elsewhere). This spread to secondary and tertiary airports and cities renders such an attack particularly alarming.

Military Application of BioWatch

Aside from considering the widespread implications of a disease, another concern is the military. For example, there are various cities through the US with large clusters of bases near the area. Newport News, VA; Colorado Springs, CO; and San Antonio are but a few cases where multiple bases utilize the nearby airport. While the four flight itinerary program can find the optimal flight path starting at these locations (or the itinerary could

be reversed to finish the attack at these locations), it would not make a great deal of sense if the goal of the attack was to infect the greatest number of US citizens or military for two reasons. First, the military makes up barely 2% of the population. For this reason, it should be obvious that the flow of military personnel does not exactly dictate which routes are more trafficked. Second, if one looked at the itinerary where an attack starts at Newport News in Table 17, it cannot be assumed that those travelling from Dallas to Los Angeles (for example) are mostly people from (or going to if the direction is reversed) the Newport News area.

Table 17. Itinerary for Three Cities with Military Bases nearby

1	2	3	4	5	Score
Newport News, VA	Atlanta, GA	Dallas, TX	Los Angeles, CA	Honolulu, HI	310,981
Colorado Springs, CO	Las Vegas, NV	Los Angeles, CA	New York City, NY (JFK)	San Juan, PR	309,543
San Antonio, TX	Dallas, TX	Atlanta, GA	Orlando, FL	Miami, FL	309,350

Table 18. Flight Itinerary for Three Cities with Military Bases nearby (BioWatch considered)

1	2	3	4	5	Score
Newport News, VA	Charlotte, NC	Dallas, TX	Denver, CO	Salt Lake City, UT	216,648
Colorado Springs, CO	Denver, CO	Salt Lake City, UT	Honolulu, HI	Kahului, HI	187,616
San Antonio, TX	Dallas, TX	Phoenix, AZ	Honolulu, HI	Kahului, HI	175,947

The only useful insight one can gain from Table 17 and Table 18 is that an attack on the Dallas/Atlanta flight might affect people trying to get to San Antonio or Newport News. A more useful source for identifying key flights and airports that could compromise the military, if the military is the target of the attack, are those in the GSA City Pair Program. By using this program, key flights can be identified for potentially

affecting the military. If key flights through this program were the focus, the net traffic on these flights could be set to significantly large number for the optimization program to pick up and likely include in its generated itineraries. For simplicity, the airports in this program were studied and organized based on how many connecting flights they had supported by the GSA in Table 19 (the entire table, in alphabetical order and by number of GSA contracted flights, are presented in the Appendix F).

Table 19. Top 20 Airports in the GSA City Pair Program

City	Airport Code	Number of GSA
ATLANTA, GA	ATL	235
WASHINGTON, DC	WAS	163
DALLAS-FT. WORTH, TX	DFW	150
WASHINGTON, DC	DCA	144
DENVER, CO	DEN	142
BOSTON, MA	BOS	128
WASHINGTON, DC	BWI	124
LOS ANGELES, CA	LAX	118
ALBUQUERQUE, NM	ABQ	107
HONOLULU, HI	HNL	101
NASHVILLE, TN	BNA	100
NEW YORK, NY	NYC	98
DETROIT, MI	DTW	93
COLUMBIA, SC	CAE	88
WASHINGTON, DC	IAD	88
COLORADO SPRINGS, CO	COS	83
ANCHORAGE, AK	ANC	81
AUSTIN, TX	AUS	80
NORFOLK, VA	ORF	80
EL PASO, TX	ELP	79

Based on Table 19, it appears that a number of airports known to have BioWatch are included. However, Dallas and Denver are part of the top five airports with the most

connecting flights. Albuquerque, Honolulu, Nashville, and Detroit, as well as other cities such as Colorado Springs, CO and Norfolk, VA are also ideal airports for impacts to large military personnel traffic (or a terrorist attack aimed at the nation's armed forces). For example, Kirtland AFB is located in Albuquerque, NM and is home to the Air Force Nuclear Weapons Center, the 58th Special Operations Wing, the Defense Threat Reduction Agency, the Air Force Operations Test and Evaluation Center, and Directed Energy Directorate, as well as several other units and organizations (U.S. Air Force, 2014). While the cost of protecting all these airports would be expensive, at least those with 100 or more connecting flights in the GSA program should be considered for BioWatch if they are not already in the program. These cities are frequently used by the military and the numerous connections reflect the large potential a deadly infection. Should one flight be compromised and not detected in time, the results would be devastating and national security could be severely impaired; this finding is further highlighted by the extensions to the Kaplan *et al*. (2002) model.

Pre-vaccination using the Kaplan-based Model

Recall in Chapter 2, Kaplan *et al*. studied the effects of mass and trace vaccination using Markov chains (Kaplan *et al.*, 2002). Using a vaccination rate of 200 vaccines per day, Kaplan *et al.* (2002) showed a significant decrease in the number of casualties and infected with a mass vaccination program. In order to reproduce their results, the model was discretized using the provided rates of change and starting conditions. In addition, notional levels of pre-vaccination were considered, as shown in Table 20.

Table 20. Comparison of Kaplan *et al.* (2002) Model and Extension

Policy	Mass Vaccination	Trace Vaccination	Discretized Model	10% Pre-Vaccination	20% Pre-Vaccination
Infected	1,830*	367,000*	369,500	314,600	125,300
Casualties	560*	110,000*	110,100	93,500	76,000
Approximate Time to Contain an Outbreak (Days)	50**	200**	200	200	200
Approximate Peak Number Infected	1,600**	130,000**	129,000	96,000	65,000
Largest Queue During Outbreak	10,000,000*	2,700**	2,800	2,000	1,300

*Based on numbers reported in the Kaplan *et al*. (2002) paper
** Based on the provided graphs (Kaplan *et al.*, 2002)

After modifying the equations, Kaplan's results are reproduced. Using this model, some valuable information can be gained (as shown in Table 20, as well as Figures 19 - 28 in Appendix A). If pre-vaccination is considered before an attack, the size of the population that is considered susceptible is reduced. Clearly, if only 20% of the population is vaccinated, the number of people infected, waiting in the queue, and or dead, drops by almost 50% (compared to the traced vaccination program). This level could be reached by vaccinating military personnel, police, fire, and hospital workers.

According to the Bureau of Labor Statistics, there are approximately 780,000 police officers employed as of May 2012 (U.S. Bureau of Labor Statistics, 2013). In addition, there are about 1.1 million firefights (both employed and volunteers) (Karter, 2013) and 18 million health care workers in the US according to the CDC (CDC, 2014). Finally, there are about 1.4 million in the military (while this number is increased by

guard and reserve numbers for about 2.3 million, the current budget situation dictates that these numbers will decline soon) (U.S Census Bureau). With a population of roughly 314 million, one can see that police, firefighters, healthcare workers, and military make up about 7% of the population.

Assuming the distribution of those in the military, police, fire, and medical community were proportionally distributed around the country, about 700,000 would exist within a city of ten million. For simplicity, if this number were rounded up to one million (10%) and all were effectively pre-vaccinated, using the extended Kaplan's model one can easily see a decrease in casualties should a smallpox attack occur. Based on the results, if 10% of the population is pre-vaccinated, the estimated number of deaths should decrease by about 16,000 to about 94,000 (15%), while the number of infected would be anticipated to drop from about 369,000 to 314,000 (15%). Although the casualties and number of infected could be reduced, it would require a larger portion of the population to be vaccinated. If those in the military, police, fire, and medical community offered to have their families vaccinated (in order to prevent an outbreak from occurring at home) or if vaccines were available to the public, it is possible that a higher percentage of pre-vaccination is obtainable. Unfortunately, should the fear of a smallpox attack cause panic, a massive demand for the smallpox vaccine could occur. If a large portion of the population were pre-vaccinated (with no attack actually occurring within five years), this large consumption of vaccines might be perceived as wasteful.

Additional Modifications of the Kaplan-based Model

Aside from looking at pre-vaccination, another modification was included in the Kaplan model. This involved changing the different factors of a disease to determine how sensitive the infection and death totals could be with a genetically engineered or altered disease. If one considers the stages of the disease, several changes should be obvious. The first is that shortening stage 1 should increase the number of deaths. Recall that stage 1 is defined as the period where there are no symptoms but a vaccine is still effective. By decreasing the amount of time a vaccine could help someone, the number of infected and dead increases. The second consideration is that decreasing the length of stage 3, when people are infectious but do not yet show signs of the disease, should reduce the number of people infected and dead. This is due to the model allowing those in stage 3 being able to infect people longer. Third, increasing the death rate of a disease, making it more virulent, should increase the number of casualties in a biological attack.

Although these modifications make sense, it is worth investigating the impact these parameters have on the model (using a population of 10 million). If the length of stage 1 is decreased by one day (for the smallpox scenario, the change is from 3 days to 2 days), the number of casualties increases by about 10,000 and the number infected increases by about 35,000. If the length of stage 3 is decreased by one day (for the smallpox scenario, the change is from 3 days to 2 days), the number of casualties decreases by about 65,000 and the number infected decreases by about 120,000. Clearly, stage 3 of the disease is a more critical factor in determining the spread and impact of an epidemic. If stage 2 or 4 is decreased by a day, there was not a noticed change as depicted in Figure 26 and Figure 28 (in Appendix A).

To better understand how much of an impact a change on several disease parameters would be, a design of experiments was conducted. By changing the 1st stage, 3rd stage, and death rate, the effects on the number of infected and dead in a population of ten million were studied. The 1st and 3rd stages had a base level of three days, with a low setting of two days and a high setting of four days in the design. Similarly, the death rate had a base level of 0.3, with a low setting of 0.2 and a high setting of 0.4. In addition, the initial number of people infected was varied (starting with an infected population of 1000, 100, and 10) and the results were compared with a 10% pre-vaccination program in place (the cases are specified in Table 21 through Table 26 in Appendix A).

While the results are summarized in Table 21 through Table 26 (in Appendix A), there are a few interesting trends. First, changing the death rate over the range in the test did not affect on the model's estimated number of people infected. Second, small parameter changes can still have a significant impact on the number of casualties and infected. If the length of stage 1 is decreased by a day, the number of infected and dead increases by 10% and 11% respectively. If it is increased by a day, the number infected and dead decrease by 7% and 8%, respectively. If the length of stage 3 is increase by a day, the number infected and dead are both increased by 50%. On the other hand, if stage 3 is decreased by a day, the estimates for the number of infected and dead decrease by 60% and 61%, respectively in the experiment design. With regards to the death rate, an increase from 0.3 to 0.4 yields a 33% increase in the estimated number dead (which makes sense since a 0.1 increase is 33% of 0.3). A decrease in the death rate to 0.2 occurs, as expected the number of dead decreases by 33%. However, changing the death rate has no impact on the number of people infected over the settings in the design of

experiments. If these factors are combined, the effect of the disease can vary significantly. The worst case in this design is if the disease decreases the length of stage 1 by a day, increases the length of stage 3 by a day, and has a death rate of 0.4 (with an initial 1,000 people infected). With these factors combined the number of infected and dead increases by 63% and 118% respectively. While the number of people initially infected was modified, it was only significant in determining the estimated number of people infected. Using the base case as a reference, the estimated number infected and casualties decreases by approximately 3,000 (0.8%) and 200 (0.2%) (respectively) when the initial number infected is changed from 1000 to 10.

With the 10% per-vaccination, the infected and dead expected can both drop by 12%. Unfortunately, this is lower than the 15% drop in the base case with a pre-vaccination program. Clearly, a pre-vaccination program can not completely suppress an outbreak with worst case characteristics. Regardless, even when the strain of smallpox is modified to produce more devastating results, the 10% pre-vaccination program still reduces the impact of an outbreak significantly (using an α value of 0.01) (hypothesis test is included in Appendix A). To visualize the different outcomes for an infection starting with 1000 people infected and no pre-vaccination program in place, Figure 17 shows the number of infected and the number dead when the parameters are changed for various cases (the cases are specified in Table 21 in Appendix A).

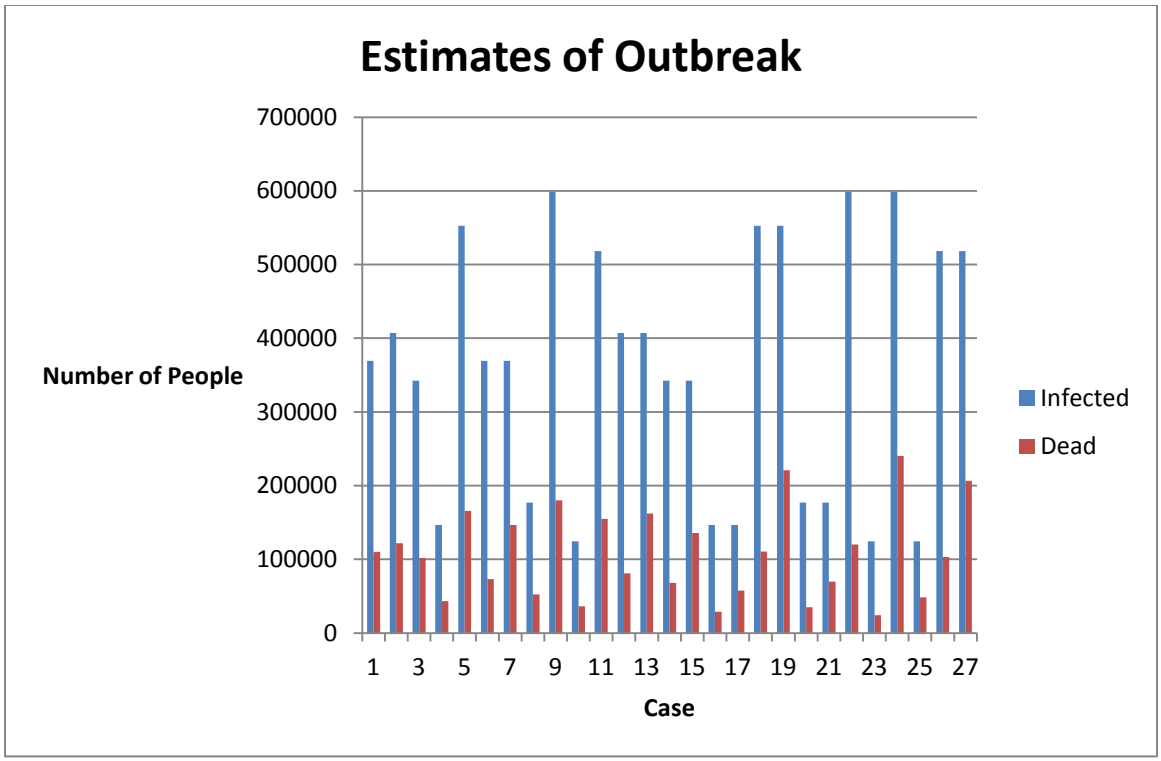

Figure 17. Estimated Outcomes for Various Scenarios in a City of 10 Million

After finding the estimated outcomes for various scenarios by modifying the length of stage 1, the length of stage 3, the death rate, and the initial number of people infected, the values were applied to a linear regression model. By conducting linear regression, the significance of the variables can be confirmed. Based on the linear model for the number of people infected, JMP determined that the length of stage 1 and 3 were statistically significant to determining the number of people infected. In addition, the initial number of people infected was important, but the death rate had no statistical significant affect on the model. This model appears reasonable based on the outcomes described earlier. In addition, the adjusted R squared is 0.99 (on a scale of zero to one with values closer to one being more desirable), indicating that any variance in the data can be explained by the linear model for small changes around the base numbers.

Once the number of infected was applied to a linear model, the number dead from an outbreak based on the various cases tested was also conducted. Based on the results, the length of stage 1, length of stage 3, and the death rate were considered significant variables. In this model, however, the initial number of people infected was not considered significant. It is hypothesized that this is due to how much impact the other variables had in determining the number of people dead from a smallpox attack compared to the initial number infected. The adjusted R squared in this regression is 0.93.

Additional linear regression models were constructed using the estimates from the pre-vaccination program. Although the estimated numbers of people infected and dead are lower in with a pre-vaccination program, the results of the linear regression models are very similar to the results without pre-vaccination. For the linear model focusing on the number of infected, the length of stage 1, the length of stage 3, and initial number infected were considered significant and had an adjusted R squared of 0.98. Likewise, the linear model for the number of people dead determined the length of stage 1, the length of stage 3, and the death rate significant, with an adjusted R squared of 0.92. Finally, all linear regression models were checked for constant variance and normally distributed residuals. All models met the assumptions and were therefore considered valid. All linear models, parameter estimates, and assumption checks are shown in Figure 29 through Figure 40 (in Appendix A).

From a biological standpoint, the characteristics of a disease, primarily stage 1 and 3, are a major concern. If these stages can be modified through genetic engineering or if a strain mutates, the impact of an epidemic can grow at alarming rates. If a disease was determined to be modified and trace vaccination was needed to contain the outbreak

(assuming a disease has not been modified to the extent that existing vaccines were ineffective), a pre-vaccination program could reduce the number of casualties and infected. If an outbreak worsened and mass vaccination was required for containment, a pre-vaccination program would reduce the number of vaccines and time needed to protect the susceptible portion of a city. Clearly, if an attack utilizes a disease with enhanced virulence, the use of bio-detection equipment and pre-vaccination (if still effective) will be needed to mitigate the casualties. Of course, these results assume a vaccine has actually been developed and is available for human use.

Military Application of Kaplan-based Model

If the extended Kaplan model is applied to a notional example, such as a smallpox attack on a community, base, or group, estimates could be generated to determine how severe the impact would be. One example is Base A, which has 40,000 personnel on base (900 of which are medical personnel) and is part of community with 110,000 additional people. If 10 people were infected on a flight and interacted with those in the community, the model predicts that about 2,700 (1.8% of the population) would be infected and 1,650 (1.1% of the population) would die from an attack out of the community of 150,000. If just those on the base were considered, about 740 (1.9% of the population) personnel are estimated to be infected and almost 450 (1.1% of the population) would die out of a group of 40,000 (assuming all other parameters are not changed).

Another scenario could involve Base B, with 5,000 personnel and 100 person medical staff. Should an attack occur, an estimated 115 (2.3% of the population) would be infected and almost 60 would die (1.2% of the population) (assuming all other

parameters are not changed). While the number infected and dead are not as severe as the Base A case, two points must be made. First, the population is constant. This means that the model assumes no one is leaving the base in order to move, complete a temporary duty assignment, or have a pass or leave elsewhere. Second, and even more critical, is the assumption that this disease is spread by the general mixing of the population. While it could be argued that units, such as pilots and finance units, operate in separate buildings and are not likely pass a disease on, there is still a large potential to contaminate the majority of personnel. This can be done by infecting security forces. At every base, security personnel check I.D.'s and essentially have brief contact with everyone entering the base. Should security personnel be infected, the entire base may be compromised. In addition, infecting food service personnel or common use areas such as the fitness center could create a vector for rapid transmission. If all military personnel were pre-vaccinated, though, the disease would not pose as critical a threat for a military installation. This again assumes a vaccine is available.

Case Study

Using the data provided by the CDC and U.S. Army Medical Department, a scenario was created of the influenza outbreak of 1918. With the CDC's information on the symptoms of influenza and assuming the Spanish flu has similar properties to the common influenza virus, the parameters of the disease can be determined. First, symptoms would not appear until 1-4 days after exposure. For simplicity, 2.5 days was used as time for stages 1-3 to occur. In addition, it is reported that a person is infectious for 1 day before showing symptoms. Based on the assumptions, this means the incubation

period is about 1.5 days. Further, the CDC reports that patients will be infective for 5-7 days once symptoms appear. Once again, for simplicity, 6 days was used as the infective period. Since the Spanish flu had a death rate greater than 2.5, 2.5 was used as a conservative estimate (CDC, 2013).

Based on information from the U.S. Army Medical Department, the report for Fort Riley, KS was used. According to the report, the base had a population of 63,374 people, 15,170 were reported to have influenza. Of those 15,170 infected, 2,624 were then reported to have pneumonia and 941 died. The infection rate was roughly 24%. The report also mentioned quarantine measure put in place once people reported to the hospital (U.S. Army Medical Department, 2004). Unfortunately, there is a concern regarding the information reported. As mentioned in the literature review, the infected number is most likely under-reported due to various reasons such as troops going AWOL, being sick on leave, and not receiving permission to report to the hospital. In addition, the Kaplan *et al*. (2002) model and its extensions are used for the general public. The military is typically more fit, reducing their susceptibility, but also can be more confined.

In order to model the scenario, several assumptions were made. First, those who died of pneumonia were treated as if they died of influenza. This is due to the inability to determine if pneumonia or influenza was the cause of death (pneumonia was probably reported once symptoms worsened). Second, while stage 3 should be 1 day based on the CDC's information, it was set at 1.5 days. This is due to how stage 3 and 4 are defined. Stage 3 is where the patient is infectious but does not show symptoms and stage 4 is where symptoms are visible. Due to the nature of smallpox, the person infected is not freely mixing with the rest of the population since the effects of the virus and the visible

signs of pox will limit how many people an infected person comes into contact with. In order to better model influenza, 1.5 days are selected for stage 3 (even though one day is how long the infection can spread from a person before symptoms appear). By setting stage 3 at 1.5 days, this assumes that those who start showing symptoms may not immediately report to the hospital. This can be due to people either trying to deal with the disease before symptoms worsen or not initially receiving permission to report to the hospital. By giving 0.5 days of the infectious period with symptoms visible to stage 3, stage 4 was shortened by 0.5 days. Stage 4 still treats the patient as if they have been removed from the population and have limited capabilities to infect others.

Using these assumptions, the population is set to 63,374 and the infection rate is (1/63,374)/(2*24). The percentage of infected is 24%, and stages 1 through 4 are set at 0.75. 0.75, 1.5, and 5.5, respectively. The initial number infected is set to 5 people and there is no effective vaccine (therefore queues and vaccination policy are not considered). The extended Kaplan model estimated 20,882 infect people and 910 people dead. While these numbers may not perfectly match the results of Fort Riley, several considerations must be addressed. With regards to the death rate, as mentioned before, 2.5% death rate was used as a conservative estimate, therefore 910 is an underestimate of the number of dead. Given the assumption, 910 is not a bad estimate for the 941 that actually died at Fort Riley.

With regards to the 20,882 people infected in the scenario, this number is assuming people report themselves to the hospital and remained on base. While half a day was added to stage 3 to make the scenario more reflective of delayed reporting, the number could be decreased if one considers people who went AWOL or started showing

symptoms and reported sick while on leave. Although the information provided in the Fort Riley report is useful, there is a great deal of potential for noise and imperfections in the data when it comes to tracking the number infected. Even if these assumptions are wrong, the model appears to overestimates the number of people infected, which is preferable to an underestimation. Although the model underestimated the casualties, it provides the minimum number dead when a conservative estimate is used. While the scenario relies on a number of assumptions, it is clear that the results are close once historical context is given to the differences.

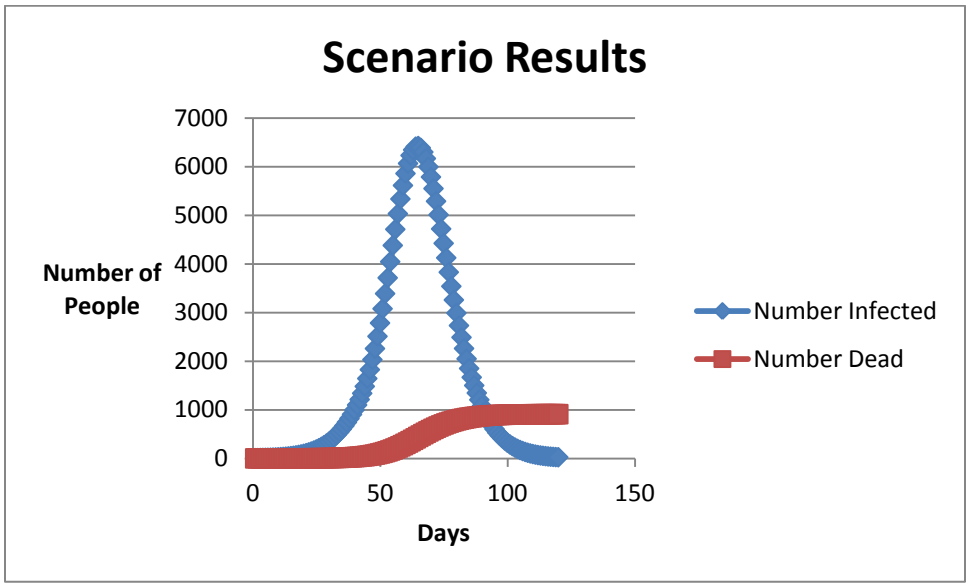

Figure 18. Influenza Model

Conclusion

Based on the results of the flight itineraries and cascade networks, network analysis identified key airports. This suggests where BioWatch should be and where protocols might be changed in a threat situation. Even if BioWatch units are avoided, certain airports would be critical targets for creating mass disruption. In the event an

attack could still occur, Kaplan *et al*.'s (2002) model provided the ability to estimate effects over a wider range of parameters. Clearly, pre-vaccination is a preferred method to mitigate the number of casualties. While it may not contain an outbreak as fast as a mass vaccination strategy, pre-vaccination assumes first responders and military are less likely to be impacted and available to help with containment. Unfortunately, if only those in the military, police, fire, and medical community, a 10% pre-vaccination rate of the population would be difficult to acquire (assuming a vaccine is available and effective against a weaponized infection). The conclusion, Chapter 5, summarizes these findings and address ideas for future research.

5. Conclusion

Introduction

While all the results will not repeated here, the major highlights of this thesis are discussed. In addition, areas for future consideration, including improvements and additional topics, are covered.

Summary

The US will always be vulnerable to a biological attack. As mentioned before, BioWatch units are limited in their abilities and numbers. Furthermore, detecting a disease does not mean its spread is stopped. However, detection does allow measures to be taken to mitigate the attack's ultimate impacts.

Using network analysis and strategically placing biodetection units at critical airports, disease outbreaks can be detected. Clearly, key airports can be identified by optimizing flight itineraries and creating cascade networks. If these key airports are not included in the BioWatch program, they should be. The high volume of traffic that flows through these airports indicates that an attack on a series of flights will result in numerous casualties. Furthermore, quarantining these airports or flight paths will disrupt the network flow. While different spread scenarios may not yield the same list of key airports, it is clear that certain airports are critical to detection. Furthermore, should these airports have BioWatch, their protocols and procedures must be effective to detect an attack quickly (and or modified if an attack is suspected).

In the event that an attack is still successfully conducted, there are ways to mitigate the spread. By pre-vaccinating a portion of the population, the number of

infected people, deaths, and size of vaccination queuing lines can be reduced. While Kaplan *et al*. (2002) argues for mass vaccination, the feasibility and limits of such a program may not be economical and present issues in defense (especially with regards to the number of effective vaccines available). By pre-vaccinating a portion of the population, the outcomes will be less severe than a trace program. In addition, should mass vaccination be called for, pre-vaccination would reduce the number of vaccines needed. Although a 10% pre-vaccination could be achieved by vaccinating military, police, fire, and medical personnel, higher percentages would yield better results. This assumes, however, a vaccine is available.

Finally, a parameterized model is now available. Using this extension to Kaplan *et al*.'s (2002) model, various parameters can be modified to predict the number of infected and casualties. Furthermore, worse case scenarios and other alterations to smallpox (or another disease similar to smallpox) can be modeled as well. Using a 10% pre-vaccination program, even in a worst case scenario (based on the parameters tested), the number of casualties and infected is reduced by 15%. This model was validated using the data from the 1918 Fort Riley report and can be adjusted for other diseases that rely on humans as a vector.

Major contributions of this research included optimizing flight itineraries and studying cascading networks to determine critical airports for disease spread. Should an outbreak still occur, by extending Kaplan's model, an alternative policy to mass and trace vaccination was provided. Furthermore, by parameterizing the model, one has greater flexibility to model outbreaks of alternate diseases and modifications to existing strains.

Future Research

While the network models above heavily relied on volume of traffic, other metrics should be studied in future research. For example, instead of using the monthly volume of traffic, flow could be determined by the aircraft used. This would give a better estimation based on the volume of traffic carried by a specific plane and provide more accurate estimations of disease spread. However, this would require additional research since there are about 75 different aircraft listed with a passenger configuration in the data. Additional research could be done into the codeshares and mergers of various airlines. Flights during other months, such as summer time, could be analyzed as well.

Another area of research that should be analyzed includes transportation networks for other means of travelling, such as by ship or subway. One example that should be considered is the network of cruise ships in the Caribbean. Some of the greater traffic volume was to Florida is due to the fact that many cruise lines operate in and out of Florida. Furthermore, a lot of cruise lines take pride in hiring people from around the world. While employees of cruise lines may not intend on spreading infectious diseases, it is possible that people from around the world operating on a cruise line could inadvertently be the origin for a disease outbreak that could impact the U.S.

One other area for future research is the global network of airports. While it is unlikely that the US will supply BioWatch units to other countries due to the cost and resources needed to manage the program, international flights could be used to spread diseases. This is especially a problem for airports that are commonly used by the U.S. citizens and armed forces overseas.

Finally, aside from additional network analysis, there is room for other improvements. One major area of improvement is spatial analysis. Unfortunately, determining second and third level infections in a network requires making numerous assumptions. If reasonable assumptions and simulations can be constructed, it is possible to generate a better picture of a disease spread throughout the country using an airport network. Another topic for consideration includes studying diseases that cannot be spread by person. For example, airport malaria could be modeled.

One other area to consider is information operations. As discussed in earlier chapters, it was assumed an infected terrorist would want to inflict mass casualties and probably avoid biodetection units. It is possible that alternate strategies, such as trying to get caught, may be an ideal strategy. By using the media and the general public's lack of knowledge in germ warfare, panic and fear could easily ensue. Clearly, there are additional scenarios and areas of research that can be studied. The threat, however, deserves further study.

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Appendix A: Kaplan's Model

Estimates for the number of people in a queue, infected, and or dead in a smallpox attack on a city of ten million people. The various tables reflect different levels of pre-vaccination.

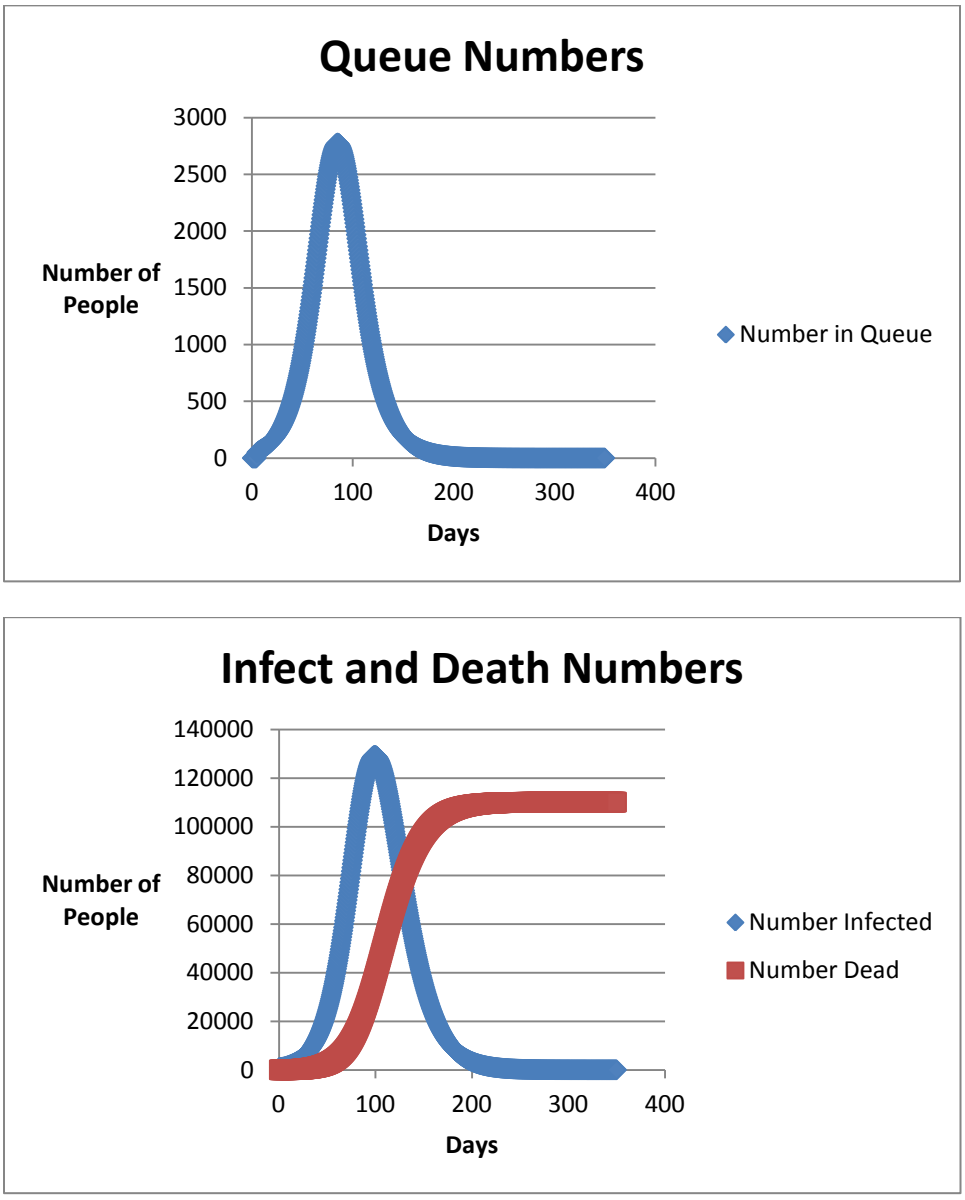
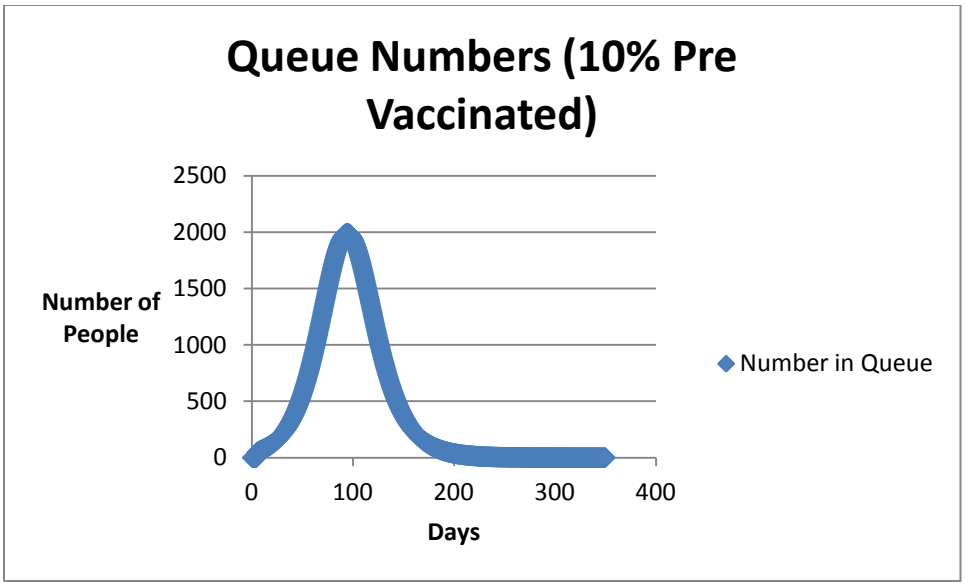


Figure 19. Estimates with no pre-vaccination



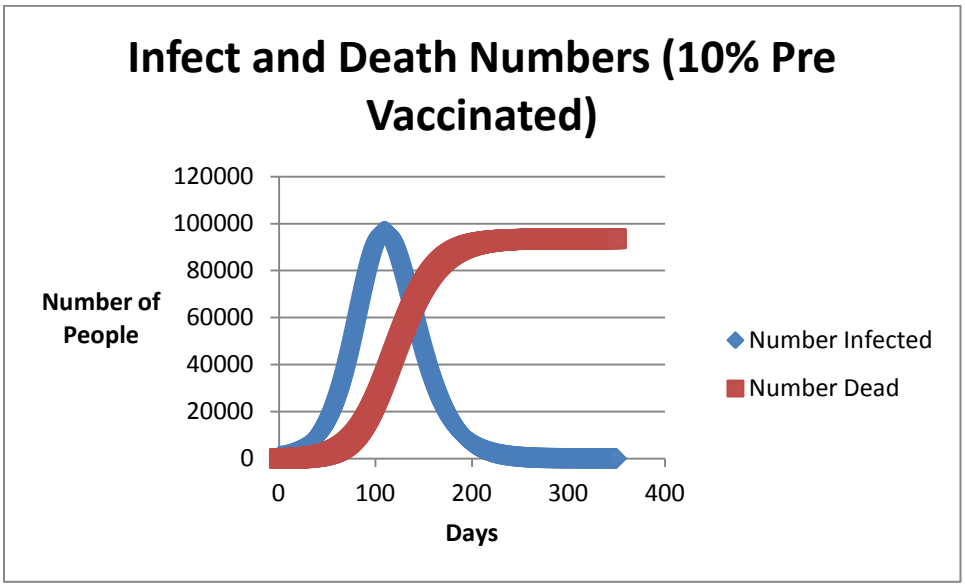
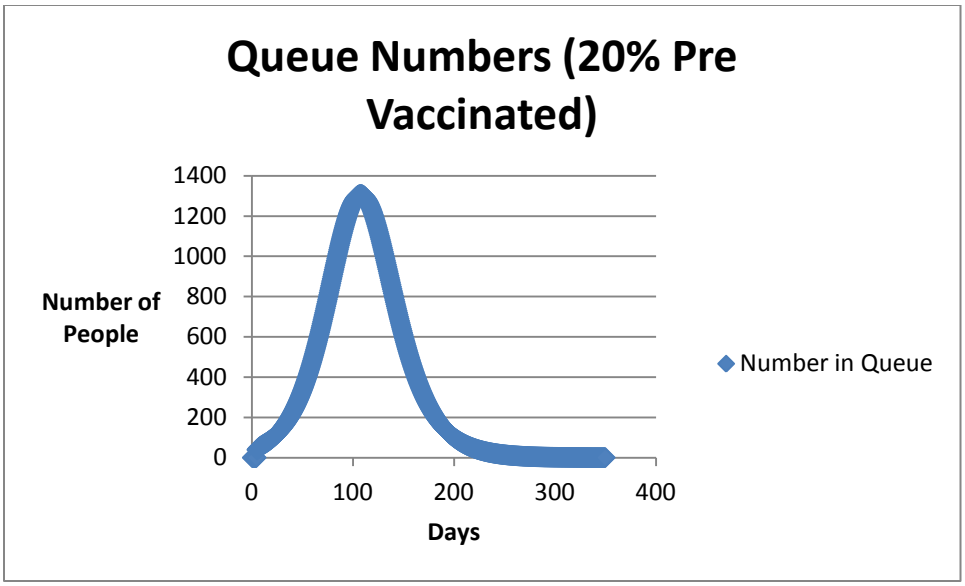


Figure 20. Estimates with 10% of the population pre-vaccinated



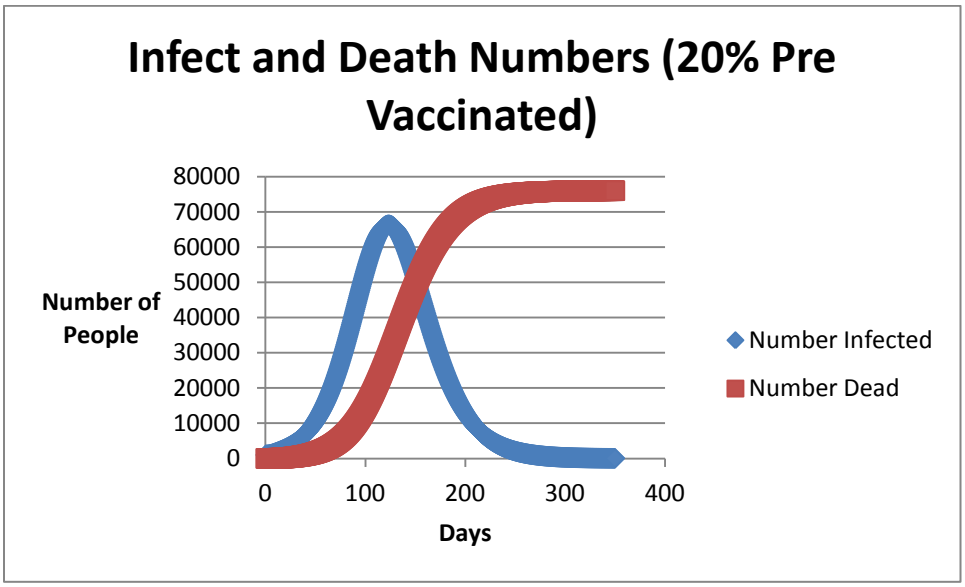
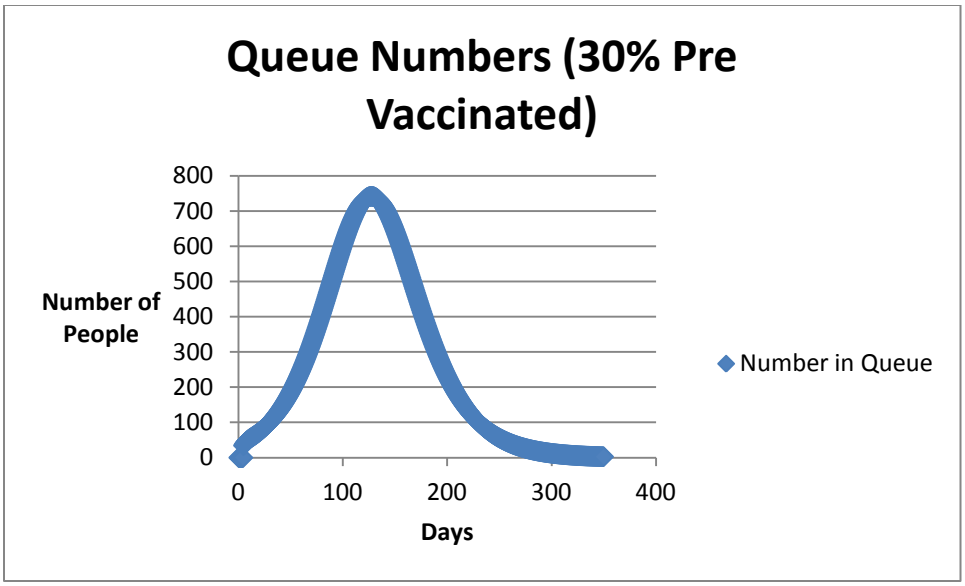


Figure 21. Estimates with 20% of the population pre-vaccinated



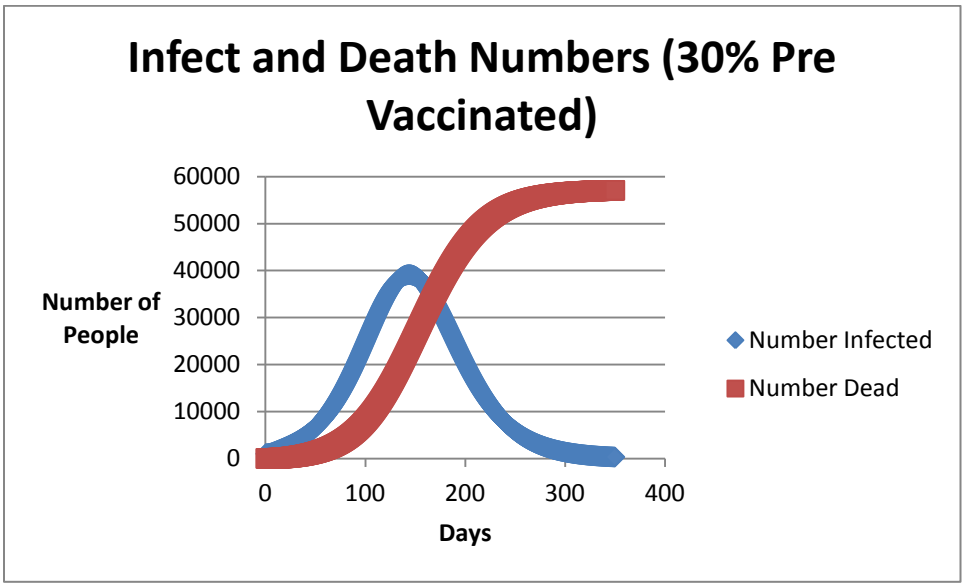
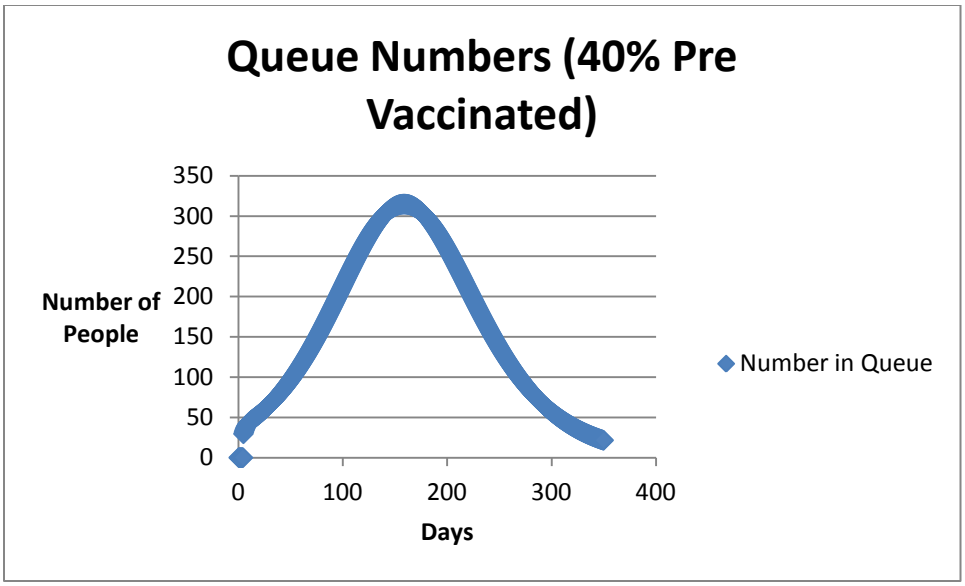


Figure 22. Estimates with 30% of the population pre-vaccinated



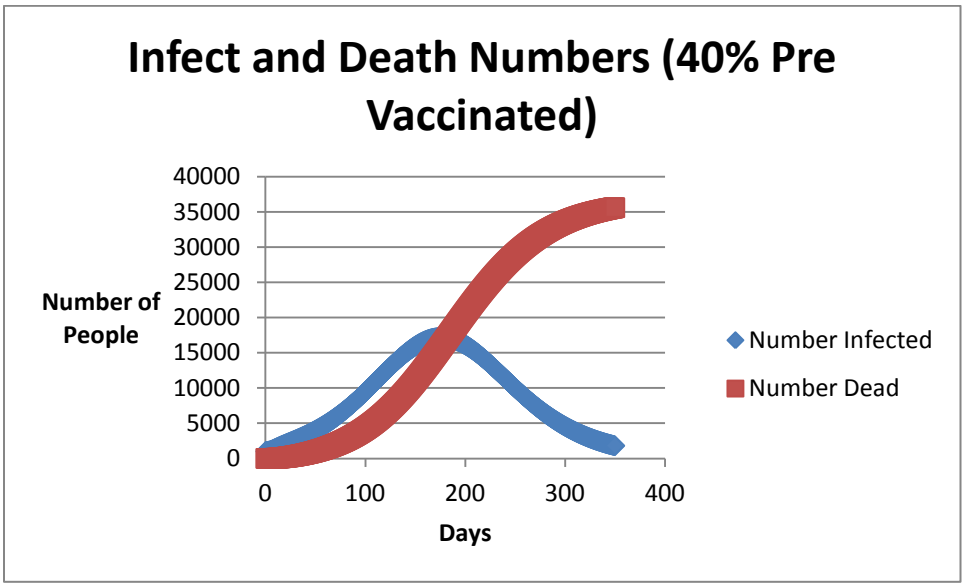
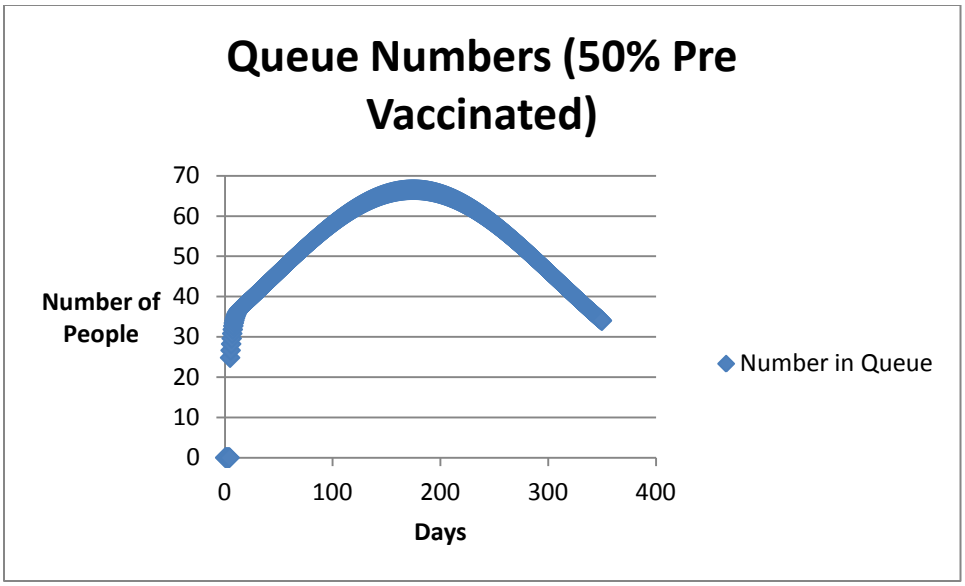


Figure 23. Estimates with 40% of the population pre-vaccinated



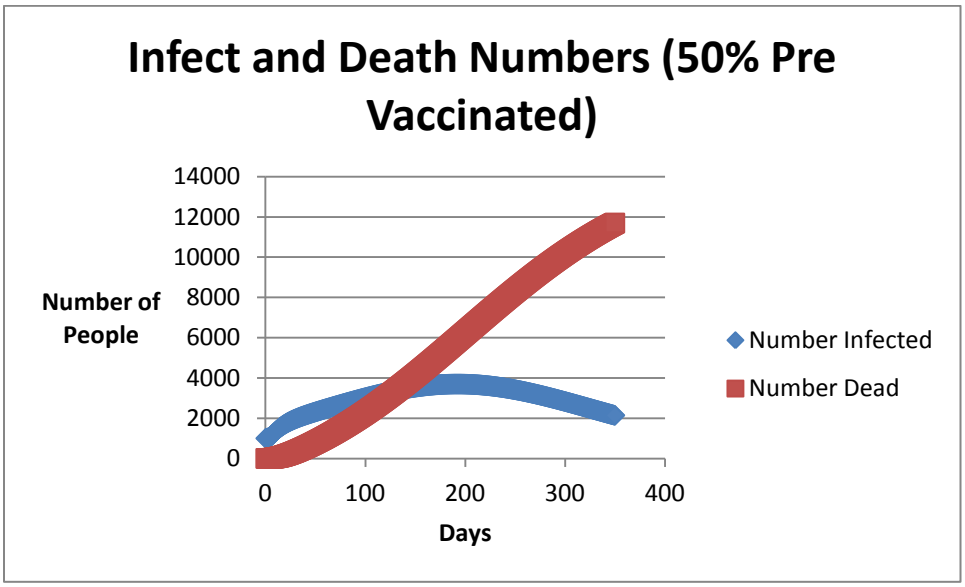


Figure 24. Estimates with 50% of the population pre-vaccinated

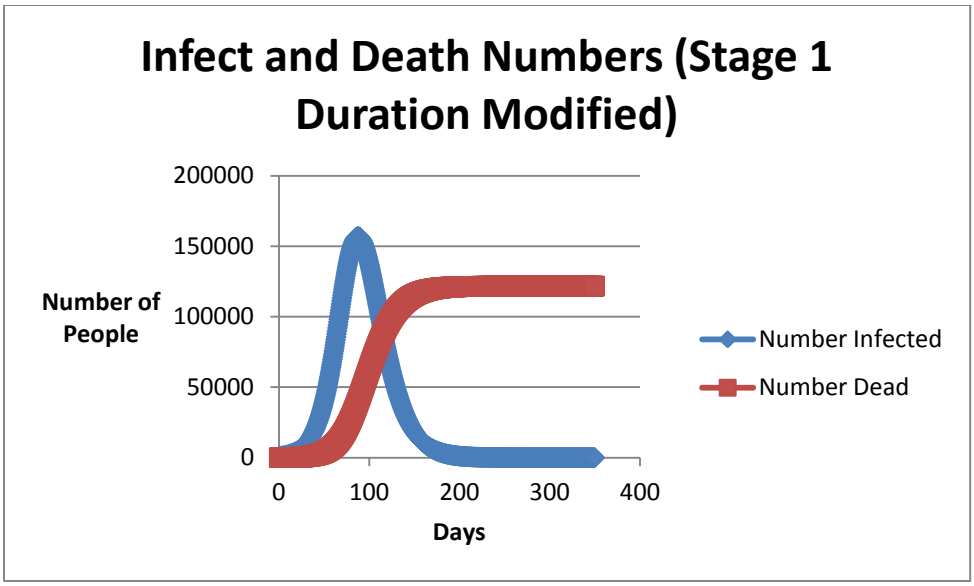


Figure 25. Estimates with Stage 1 Decreases by 1 Day

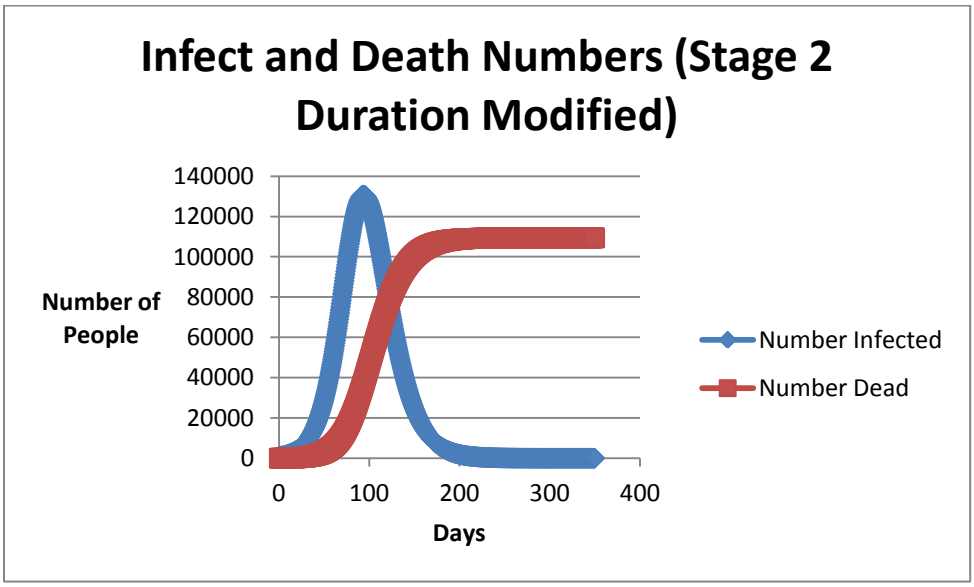


Figure 26. Estimates with Stage 2 Decreased by 1 Day

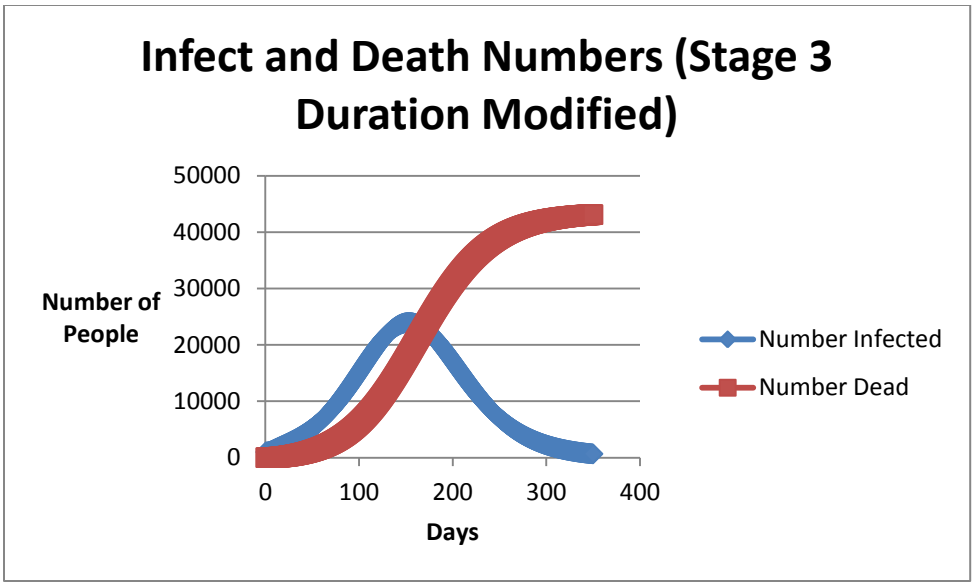


Figure 27. Estimates with Stage 3 Decreased by 1 Day

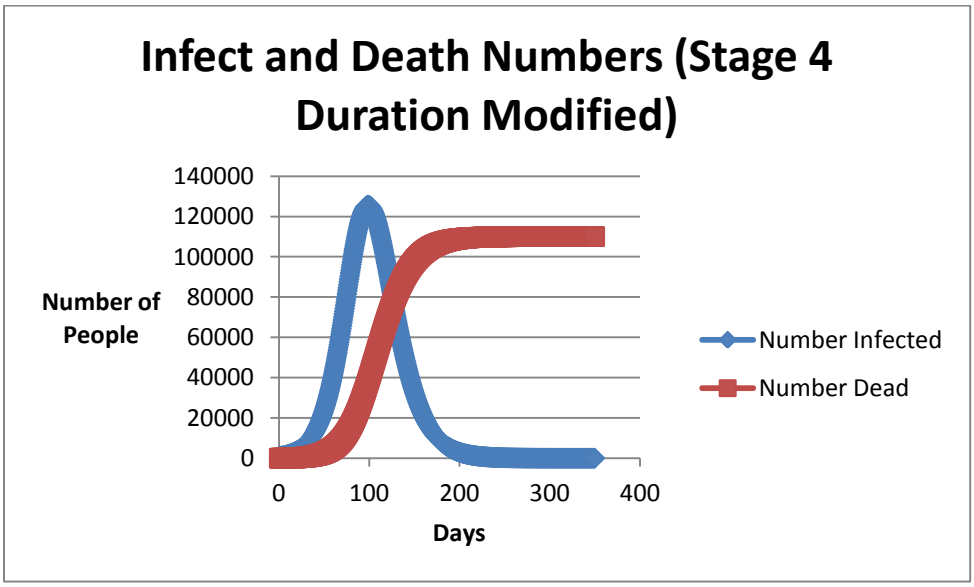


Figure 28. Estimates with Stage 4 Decreased by 1 Day

Below are tables documenting the estimated number of infected and dead for 1000, 100, and 10 people initially infected based on results from the extended Kaplan model. Also displays the percentage change from the base case, as well as with the pre- vaccination program.

Table 21. Infected and Death Numbers (Start with 1000 Infected)

Case	Stage 1 (Days)	Stage 3 (Days)	Death Rate	Infected	Dead	% Change Infected	% Change Dead
1	3	3	0.3	369,542	110,092	0%	0%
2	2	3	0.3	406,979	121,689	10%	11%
3	4	3	0.3	342,625	101,800	-7%	-8%
4	3	2	0.3	146,716	43,112	-60%	-61%
5	3	4	0.3	552,642	165,598	50%	50%
6	3	3	0.2	369,542	73,395	0%	-33%
7	3	3	0.4	369,542	146,790	0%	33%
8	2	2	0.3	176,853	52,377	-52%	-52%
9	2	4	0.3	599,169	180,151	62%	64%
10	4	2	0.3	124,389	36,211	-66%	-67%
11	4	4	0.3	518,331	154,913	40%	41%
12	2	3	0.2	406,979	81,126	10%	-26%
13	2	3	0.4	406,979	162,251	10%	47%
14	4	3	0.2	342,625	67,867	-7%	-38%
15	4	3	0.4	342,625	135,733	-7%	23%
16	3	2	0.2	146,716	28,741	-60%	-74%
17	3	2	0.4	146,716	57,483	-60%	-48%
18	3	4	0.2	552,642	110,399	50%	0%
19	3	4	0.4	552,642	220,797	50%	101%
20	2	2	0.2	176,853	34,918	-52%	-68%
21	2	2	0.4	176,853	69,836	-52%	-37%
22	2	4	0.2	599,169	120,101	62%	9%
23	4	2	0.2	124,389	24,141	-66%	-78%
24	2	4	0.4	599,169	240,201	62%	118%
25	4	2	0.4	124,389	48,282	-66%	-56%
26	4	4	0.2	518,331	103,276	40%	-6%
27	4	4	0.4	518,331	206,551	40%	88%

*Case 1 is the base case presented in Kaplan's paper (2002)
** Percentage change are in comparison to the base case (case 1)

Table 22. Infected and Death Numbers (Start with 100 Infected)

Case	Stage 1	Stage 3	Death Rate	Infected	Dead	% Change Infected	% Change Dead
1	3	3	0.3	366,722	109,795	0%	0%
2	2	3	0.3	404,569	121,411	10%	11%
3	4	3	0.3	339,533	101,475	-7%	-8%
4	3	2	0.3	133,770	39,230	-64%	-64%
5	3	4	0.3	550,084	165,389	50%	51%
6	3	3	0.2	366,722	73,197	0%	-33%
7	3	3	0.4	366,722	146,393	0%	33%
8	2	2	0.3	172,033	51,250	-53%	-53%
9	2	4	0.3	596,973	179,947	63%	64%
10	4	2	0.3	94,987	27,020	-74%	-75%
11	4	4	0.3	515,568	154,702	41%	41%
12	2	3	0.2	404,569	80,941	10%	-26%
13	2	3	0.4	404,569	161,881	10%	47%
14	4	3	0.2	339,533	67,650	-7%	-38%
15	4	3	0.4	339,533	135,299	-7%	23%
16	3	2	0.2	133,770	26,153	-64%	-76%
17	3	2	0.4	133,770	52,307	-64%	-52%
18	3	4	0.2	550,084	110,259	50%	0%
19	3	4	0.4	550,084	220,518	50%	101%
20	2	2	0.2	172,033	34,167	-53%	-69%
21	2	2	0.4	172,033	68,334	-53%	-38%
22	2	4	0.2	596,973	119,965	63%	9%
23	4	2	0.2	94,987	18,013	-74%	-84%
24	2	4	0.4	596,973	239,929	63%	119%
25	4	2	0.4	94,987	36,027	-74%	-67%
26	4	4	0.2	515,568	103,135	41%	-6%
27	4	4	0.4	515,568	206,269	41%	88%

*Case 1 is the base case presented in Kaplan's paper (2002)

** Percentage change are in comparison to the base case (case 1)

Table 23. Infected and Death Numbers (Start with 10 Infected)

Case	Stage 1	Stage 3	Death Rate	Infected	Dead	% Change Infected	% Change Dead
1	3	3	0.3	366,402	109,747	0%	0%
2	2	3	0.3	404,325	121,382	10%	11%
3	4	3	0.3	338,967	101,322	-7%	-8%
4	3	2	0.3	88,905	24,352	-76%	-78%
5	3	4	0.3	549,827	165,368	50%	51%
6	3	3	0.2	366,402	73,165	0%	-33%
7	3	3	0.4	366,402	146,329	0%	33%
8	2	2	0.3	162,053	47,566	-56%	-57%
9	2	4	0.3	596,753	179,926	63%	64%
10	4	2	0.3	33,340	8,649	-91%	-92%
11	4	4	0.3	515,287	154,679	41%	41%
12	2	3	0.2	404,325	80,921	10%	-26%
13	2	3	0.4	404,325	161,842	10%	47%
14	4	3	0.2	338,967	67,548	-7%	-38%
15	4	3	0.4	338,967	135,095	-7%	23%
16	3	2	0.2	88,905	16,235	-76%	-85%
17	3	2	0.4	88,905	32,470	-76%	-70%
18	3	4	0.2	549,827	110,245	50%	0%
19	3	4	0.4	549,827	220,490	50%	101%
20	2	2	0.2	162,053	31,711	-56%	-71%
21	2	2	0.4	162,053	63,421	-56%	-42%
22	2	4	0.2	596,753	119,951	63%	9%
23	4	2	0.2	33,340	5,766	-91%	-95%
24	2	4	0.4	596,753	239,902	63%	119%
25	4	2	0.4	33,340	11,532	-91%	-89%
26	4	4	0.2	515,287	103,119	41%	-6%
27	4	4	0.4	515,287	206,238	41%	88%

*Case 1 is the base case presented in Kaplan's paper (2002)

** Percentage change are in comparison to the base case (case 1)

Table 24.Infected and Death Numbers (Start with 1000 Infected) with Pre-Vaccination

Case	Stage 1 (Days)	Stage 3 (Days)	Death Rate	Infected	Dead	Infected with PreVac	Dead with PreVac	% Change Infected	% Change Dead
1	3	3	0.3	369,542	110,092	314,359	93,549	-15%	-15%
2	2	3	0.3	406,979	121,689	348,587	104,139	-14%	-14%
3	4	3	0.3	342,625	101,800	289,639	85,942	-15%	-16%
4	3	2	0.3	146,716	43,112	97,776	28,381	-33%	-34%
5	3	4	0.3	552,642	165,598	487,581	145,997	-12%	-12%
6	3	3	0.2	369,542	73,395	314,359	62,366	-15%	-15%
7	3	3	0.4	369,542	146,790	314,359	124,732	-15%	-15%
8	2	2	0.3	176,853	52,377	128,440	37,854	-27%	-28%
9	2	4	0.3	599,169	180,151	529,146	158,994	-12%	-12%
10	4	2	0.3	124,389	36,211	74,472	21,215	-40%	-41%
11	4	4	0.3	518,331	154,913	456,767	136,409	-12%	-12%
12	2	3	0.2	406,979	81,126	348,587	69,426	-14%	-14%
13	2	3	0.4	406,979	162,251	348,587	138,852	-14%	-14%
14	4	3	0.2	342,625	67,867	289,639	57,295	-15%	-16%
15	4	3	0.4	342,625	135,733	289,639	114,589	-15%	-16%
16	3	2	0.2	146,716	28,741	97,776	18,921	-33%	-34%
17	3	2	0.4	146,716	57,483	97,776	37,841	-33%	-34%
18	3	4	0.2	552,642	110,399	487,581	97,331	-12%	-12%
19	3	4	0.4	552,642	220,797	487,581	194,662	-12%	-12%
20	2	2	0.2	176,853	34,918	128,440	25,236	-27%	-28%
21	2	2	0.4	176,853	69,836	128,440	50,473	-27%	-28%
22	2	4	0.2	599,169	120,101	529,146	105,996	-12%	-12%
23	4	2	0.2	124,389	24,141	74,472	14,143	-40%	-41%
24	2	4	0.4	599,169	240,201	529,146	211,992	-12%	-12%
25	4	2	0.4	124,389	48,282	74,472	28,287	-40%	-41%
26	4	4	0.2	518,331	103,276	456,767	90,939	-12%	-12%
27	4	4	0.4	518,331	206,551	456,767	181,878	-12%	-12%

*Case 1 is the base case presented in Kaplan's paper (2002)

** Percentage change reflects the difference when a 10% pre-vaccination program is in place compared to no vaccination program.

Table 25. Infected and Death Numbers (Start with 100 Infected) with Pre-Vaccination

Case	Stage 1	Stage 3	Death Rate	Infected	Dead	Infected with PreVac	Dead with PreVac	% Change Infected	% Change Dead
1	3	3	0.3	366,722	109,795	311,367	93,190	-15%	-15%
2	2	3	0.3	404,569	121,411	346,062	103,819	-14%	-14%
3	4	3	0.3	339,533	101,475	286,198	85,483	-16%	-16%
4	3	2	0.3	133,770	39,230	62,923	17,737	-53%	-55%
5	3	4	0.3	550,084	165,389	484,968	145,765	-12%	-12%
6	3	3	0.2	366,722	73,197	311,367	62,127	-15%	-15%
7	3	3	0.4	366,722	146,393	311,367	124,253	-15%	-15%
8	2	2	0.3	172,033	51,250	114,992	33,756	-33%	-34%
9	2	4	0.3	596,973	179,947	526,906	158,769	-12%	-12%
10	4	2	0.3	94,987	27,020	29,708	8,155	-69%	-70%
11	4	4	0.3	515,568	154,702	453,937	136,172	-12%	-12%
12	2	3	0.2	404,569	80,941	346,062	69,213	-14%	-14%
13	2	3	0.4	404,569	161,881	346,062	138,426	-14%	-14%
14	4	3	0.2	339,533	67,650	286,198	56,989	-16%	-16%
15	4	3	0.4	339,533	135,299	286,198	113,977	-16%	-16%
16	3	2	0.2	133,770	26,153	62,923	11,825	-53%	-55%
17	3	2	0.4	133,770	52,307	62,923	23,649	-53%	-55%
18	3	4	0.2	550,084	110,259	484,968	97,177	-12%	-12%
19	3	4	0.4	550,084	220,518	484,968	194,353	-12%	-12%
20	2	2	0.2	172,033	34,167	114,992	22,504	-33%	-34%
21	2	2	0.4	172,033	68,334	114,992	45,008	-33%	-34%
22	2	4	0.2	596,973	119,965	526,906	105,846	-12%	-12%
23	4	2	0.2	94,987	18,013	29,708	5,437	-69%	-70%
24	2	4	0.4	596,973	239,929	526,906	211,692	-12%	-12%
25	4	2	0.4	94,987	36,027	29,708	10,873	-69%	-70%
26	4	4	0.2	515,568	103,135	453,937	90,781	-12%	-12%
27	4	4	0.4	515,568	206,269	453,937	181,562	-12%	-12%

*Case 1 is the base case presented in Kaplan's paper (2002)

** Percentage change reflects the difference when a 10% pre-vaccination program is in place compared to no vaccination program.

Table 26. Infected and Death Numbers (Start with 10 Infected) with Pre-Vaccination

Case	Stage 1	Stage 3	Death Rate	Infected	Dead	Infected with PreVac	Dead with PreVac	% Change Infected	% Change Dead
1	3	3	0.3	366,402	109,747	310,816	93,038	-15%	-15%
2	2	3	0.3	404,325	121,382	345,786	103,776	-14%	-15%
3	4	3	0.3	338,967	101,322	284,341	84,771	-16%	-16%
4	3	2	0.3	88,905	24,352	15,568	4,091	-82%	-83%
5	3	4	0.3	549,827	165,368	484,704	145,740	-12%	-12%
6	3	3	0.2	366,402	73,165	310,816	62,026	-15%	-15%
7	3	3	0.4	366,402	146,329	310,816	124,051	-15%	-15%
8	2	2	0.3	162,053	47,566	70,497	19,339	-56%	-59%
9	2	4	0.3	596,753	179,926	526,682	158,747	-12%	-12%
10	4	2	0.3	33,340	8,649	4,456	1,181	-87%	-86%
11	4	4	0.3	515,287	154,679	453,635	136,138	-12%	-12%
12	2	3	0.2	404,325	80,921	345,786	69,184	-14%	-15%
13	2	3	0.4	404,325	161,842	345,786	138,368	-14%	-15%
14	4	3	0.2	338,967	67,548	284,341	56,514	-16%	-16%
15	4	3	0.4	338,967	135,095	284,341	113,028	-16%	-16%
16	3	2	0.2	88,905	16,235	15,568	2,727	-82%	-83%
17	3	2	0.4	88,905	32,470	15,568	5,455	-82%	-83%
18	3	4	0.2	549,827	110,245	484,704	97,160	-12%	-12%
19	3	4	0.4	549,827	220,490	484,704	194,320	-12%	-12%
20	2	2	0.2	162,053	31,711	70,497	12,893	-56%	-59%
21	2	2	0.4	162,053	63,421	70,497	25,786	-56%	-59%
22	2	4	0.2	596,753	119,951	526,682	105,831	-12%	-12%
23	4	2	0.2	33,340	5,766	4,456	787	-87%	-86%
24	2	4	0.4	596,753	239,902	526,682	211,662	-12%	-12%
25	4	2	0.4	33,340	11,532	4,456	1,575	-87%	-86%
26	4	4	0.2	515,287	103,119	453,635	90,759	-12%	-12%
27	4	4	0.4	515,287	206,238	453,635	181,517	-12%	-12%

*Case 1 is the base case presented in Kaplan's paper (2002)

** Percentage change reflects the difference when a 10% pre-vaccination program is in place compared to no vaccination program.

The outcomes for the case scenarios on Base A and Base B are presented here. The parameters that were changed (compared to the base case used in Dr. Kaplan's paper (2002)) are also specified. The first case relies on the same values used by Dr. Kaplan for the length of stage 1, the length of stage 3, and the death rate. All additional cases included in the table are various scenarios should the disease be slightly modified by either genetic engineering or mutation.

Base A (with community)

N (Population size) =150,000 NV (Number of vaccinators) = 900

Beta (Rate infected) = (1/150,000)/(2*24) IZero (Initial number infected) = 10

Table 27. Infected and Death Numbers For Base A (population of 150,000)

Case	Stage 1 (Days)	Stage 3 (Days)	Death Rate	Infected	Dead
1	3	3	0.3	2,695	1,650
2	2	3	0.3	3,072	1,824
3	4	3	0.3	2,423	1,525
4	3	2	0.3	1,064	640
5	3	4	0.3	4,032	2,483
6	3	3	0.2	2,695	1,100
7	3	3	0.4	2,695	2,200
8	2	2	0.3	1,334	782
9	2	4	0.3	4,521	2,701
10	4	2	0.3	865	529
11	4	4	0.3	3,671	2,323
12	2	3	0.2	3,072	1,216
13	2	3	0.4	3,072	2,432
14	4	3	0.2	2,423	1,017
15	4	3	0.4	2,423	2,034
16	3	2	0.2	1,064	426
17	3	2	0.4	1,064	853
18	3	4	0.2	4,032	1,655
19	3	4	0.4	4,032	3,310
20	2	2	0.2	1,334	521
21	2	2	0.4	1,334	1,042
22	2	4	0.2	4,521	1,801
23	4	2	0.2	865	353
24	2	4	0.4	4,521	3,602
25	4	2	0.4	865	705
26	4	4	0.2	3,671	1,548
27	4	4	0.4	3,671	3,097

Base A (without community)

N (Population size) =40,000 NV (Number of vaccinators) = 900

Beta (Rate infected) = (1/40,000)/(2*24) IZero (Initial number infected) = 10

Table 28. Infected and Death Numbers For Base A (population of 40,000)

Case	Stage 1 (Days)	Stage 3 (Days)	Death Rate	Infected	Dead
1	3	3	0.3	738	442
2	2	3	0.3	836	489
3	4	3	0.3	668	409
4	3	2	0.3	311	178
5	3	4	0.3	1,094	664
6	3	3	0.2	738	295
7	3	3	0.4	738	590
8	2	2	0.3	376	214
9	2	4	0.3	1,221	722
10	4	2	0.3	267	154
11	4	4	0.3	1,000	621
12	2	3	0.2	836	326
13	2	3	0.4	836	651
14	4	3	0.2	668	273
15	4	3	0.4	668	546
16	3	2	0.2	311	119
17	3	2	0.4	311	238
18	3	4	0.2	1,094	443
19	3	4	0.4	1,094	885
20	2	2	0.2	376	142
21	2	2	0.4	376	285
22	2	4	0.2	1,221	481
23	4	2	0.2	267	102
24	2	4	0.4	1,221	963
25	4	2	0.4	267	205
26	4	4	0.2	1,000	414
27	4	4	0.4	1,000	828

Base B

N (Population size)=5000 NV (Number of vaccinators) =100

Beta (Rate infected) = (1/5000)/(2*24) IZero (Initial number infected) =10

Table 29. Infected and Death Numbers For Base B (population of 5,000)

Case	Stage 1 (Days)	Stage 3 (Days)	Death Rate	Infected	Dead
1	3	3	0.3	116	58
2	2	3	0.3	124	64
3	4	3	0.3	109	54
4	3	2	0.3	66	28
5	3	4	0.3	159	85
6	3	3	0.2	116	39
7	3	3	0.4	116	77
8	2	2	0.3	70	32
9	2	4	0.3	171	92
10	4	2	0.3	64	25
11	4	4	0.3	150	80
12	2	3	0.2	124	42
13	2	3	0.4	124	85
14	4	3	0.2	109	36
15	4	3	0.4	109	72
16	3	2	0.2	66	19
17	3	2	0.4	66	37
18	3	4	0.2	159	57
19	3	4	0.4	159	113
20	2	2	0.2	70	21
21	2	2	0.4	70	42
22	2	4	0.2	171	61
23	4	2	0.2	64	17
24	2	4	0.4	171	123
25	4	2	0.4	64	34
26	4	4	0.2	150	53
27	4	4	0.4	150	106

Linear Regression of the Model Parameter Values and the Expected Outcomes

Using linear regression, the various values of the death rate, length of stage 1, length of stage 3, and initial number of infected people were used to determine the key variables. Figure 29 displays the linear regression model of the number infected, while Figure 30 shows the parameter estimates and their significance. The Residual by Predicted Plot in Figure 30 and the quantile plot in Figure 31 are used to confirm that the needed assumptions are met for linear regression.

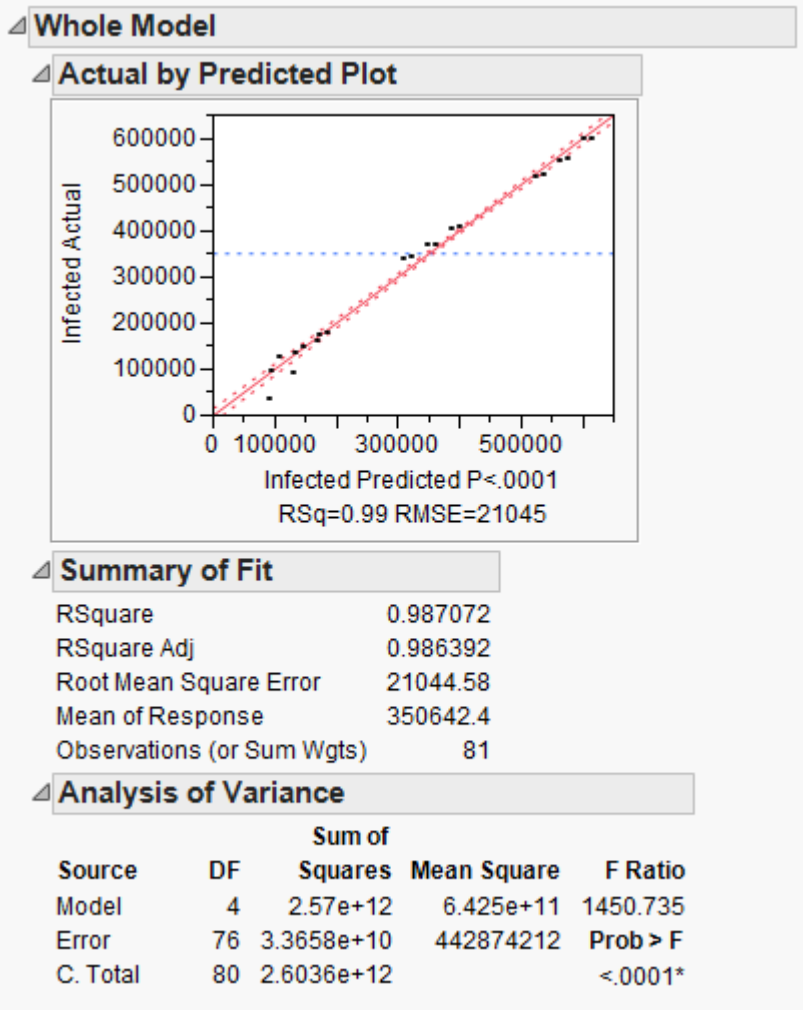


Figure 29. Linear Regression Model of Number Infected

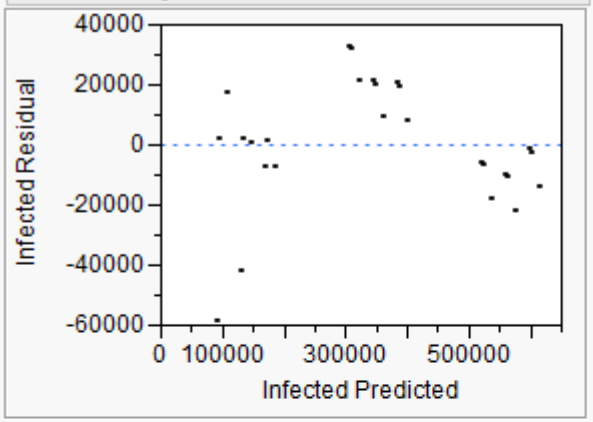
Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|	VIF
Intercept	-182487.8	15187.2	-12.02	<.0001*	.
Stage1	-38704.44	2863.804	-13.52	<.0001*	1
Stage 3	214532.67	2863.804	74.91	<.0001*	1
Death Rate	6.928e-12	28638.04	0.00	1.0000	1
Initial Infected	15.258075	5.231183	2.92	0.0046*	1

Effect Tests

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
Stage1	1	1	8.0894e+10	182.6565	<.0001*
Stage 3	1	1	2.4853e+12	5611.775	<.0001*
Death Rate	1	1	2.5921e-23	0.0000	1.0000
Initial Infected	1	1	3767731783	8.5075	0.0046*

Residual by Predicted Plot



Correlation of Estimates

Corr

	Intercept	Stage1	Stage 3	Death Rate	Initial Infected
Intercept	1.0000	-0.5657	-0.5657	-0.5657	-0.1274
Stage1	-0.5657	1.0000	0.0000	0.0000	0.0000
Stage 3	-0.5657	0.0000	1.0000	0.0000	0.0000
Death Rate	-0.5657	0.0000	0.0000	1.0000	0.0000
Initial Infected	-0.1274	0.0000	0.0000	0.0000	1.0000

Figure 30. Linear Regression Model of Number Infected (Parameters)

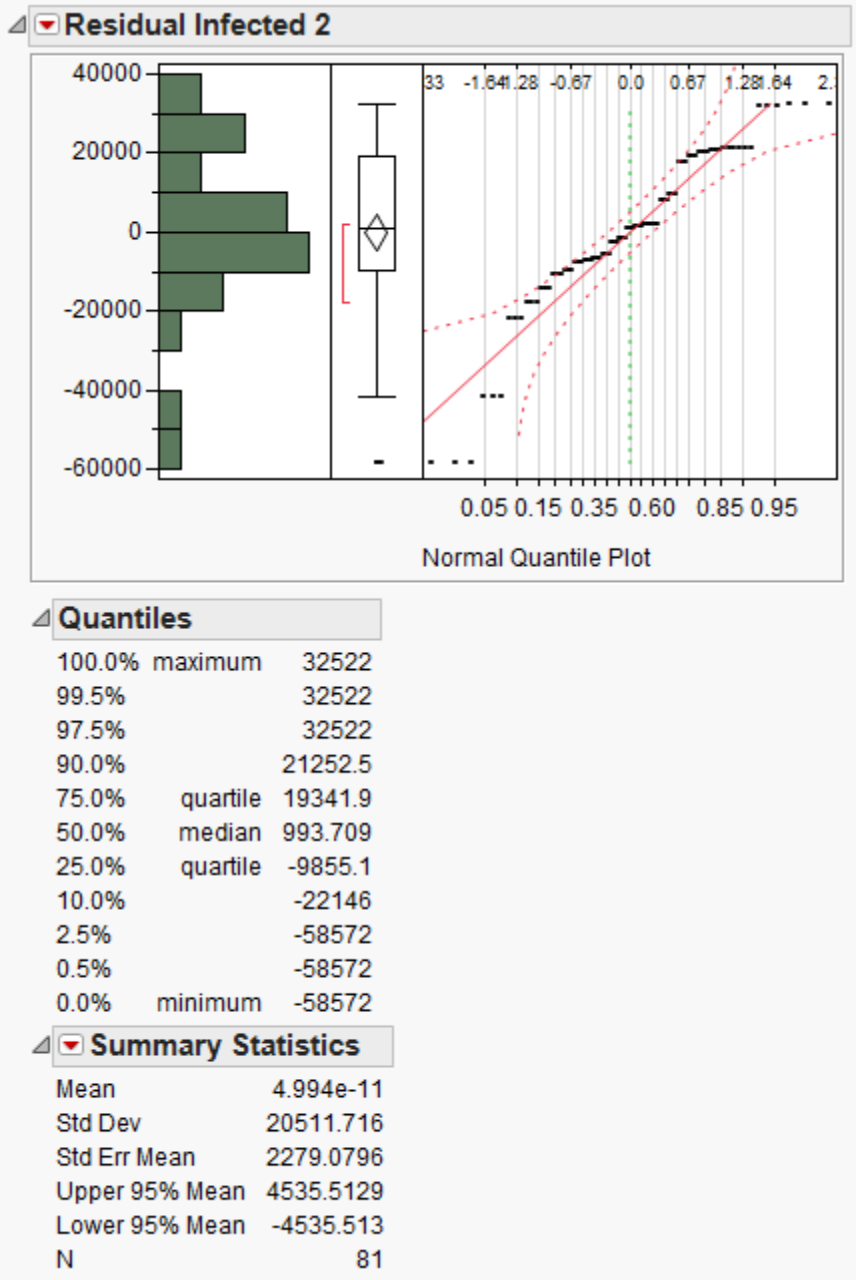
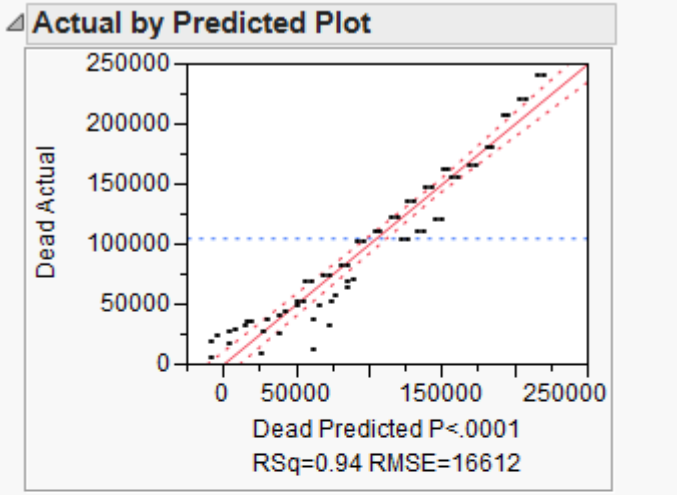


Figure 31. Distribution of Errors from Linear Regression Model for Number Infected

Figure 32 displays the linear regression model of the number dead, while Figure 33 shows the parameter estimates and their significance. The Residual by Predicted Plot

in Figure 33 and the quantile plot in Figure 34 are used to confirm that the needed assumptions are met for linear regression.



Summary of Fit

RSquare	0.935137
RSquare Adj	0.931723
Root Mean Square Error	16612.4
Mean of Response	104783.4
Observations (or Sum Wgts)	81

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	4	3.0238e+11	7.56e+10	273.9238
Error	76	2.0974e+10	275971879	Prob > F
C. Total	80	3.2335e+11		<.0001*

Figure 32. Linear Regression Model of Number Dead

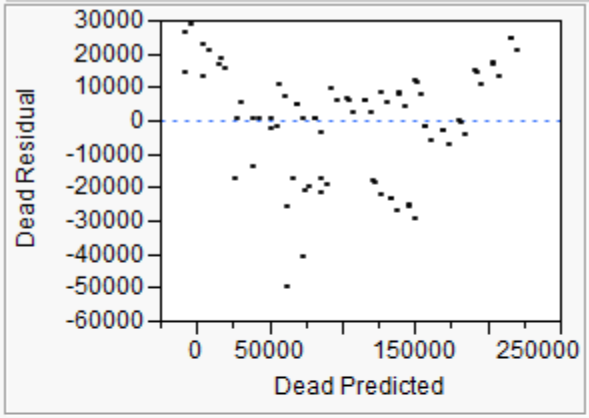
Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|	VIF
Intercept	-160927.7	11988.64	-13.42	<.0001*	.
Stage1	-11940.46	2260.661	-5.28	<.0001*	1
Stage 3	65050.259	2260.661	28.77	<.0001*	1
Death Rate	349276.85	22606.61	15.45	<.0001*	1
Initial Infected	4.320793	4.12945	1.05	0.2987	1

Effect Tests

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
Stage1	1	1	7699031412	27.8979	<.0001*
Stage 3	1	1	2.285e+11	827.9936	<.0001*
Death Rate	1	1	6.5877e+10	238.7089	<.0001*
Initial Infected	1	1	302139445	1.0948	0.2987

Residual by Predicted Plot



Correlation of Estimates

Corr

	Intercept	Stage1	Stage 3	Death Rate	Initial Infected
Intercept	1.0000	-0.5657	-0.5657	-0.5657	-0.1274
Stage1	-0.5657	1.0000	0.0000	0.0000	0.0000
Stage 3	-0.5657	0.0000	1.0000	0.0000	0.0000
Death Rate	-0.5657	0.0000	0.0000	1.0000	0.0000
Initial Infected	-0.1274	0.0000	0.0000	0.0000	1.0000

Figure 33. Linear Regression Model of Number Dead (Parameters)

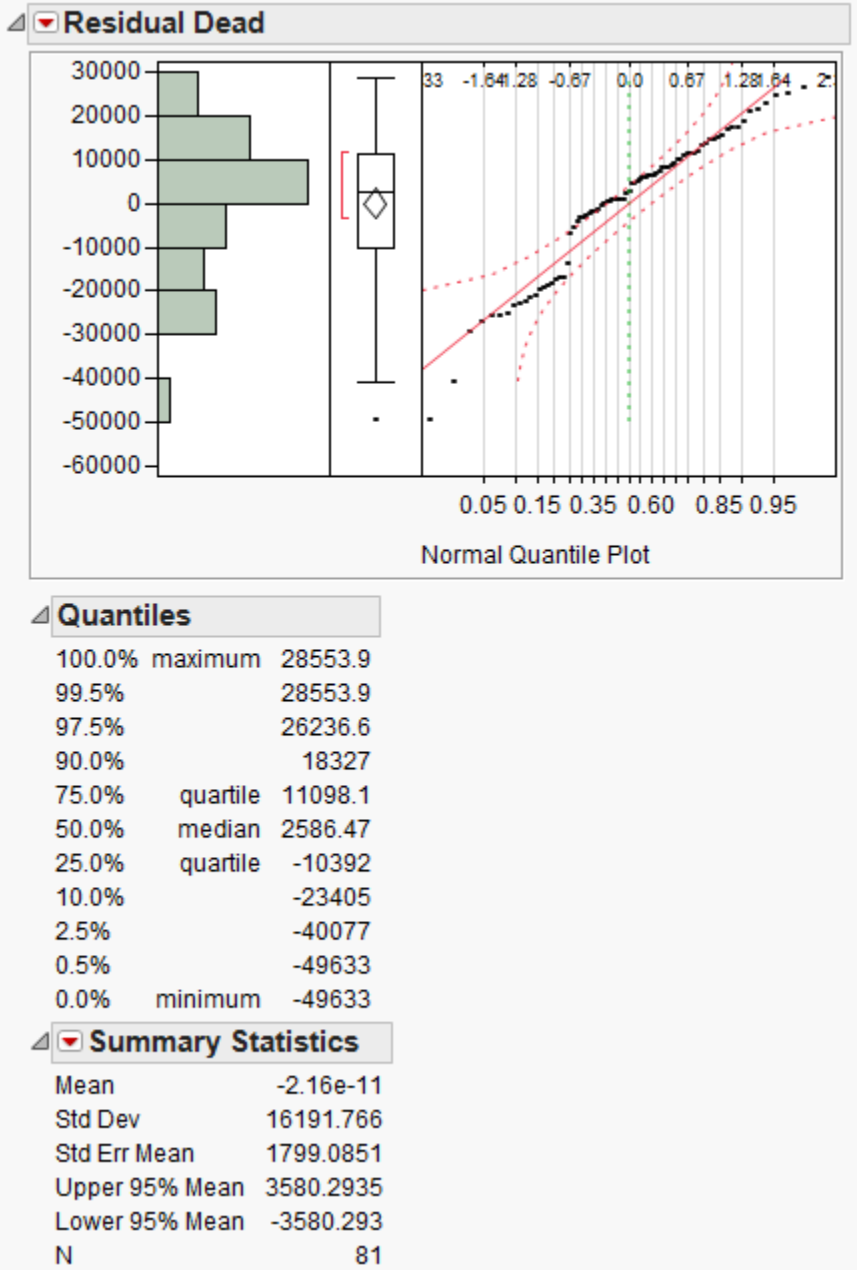
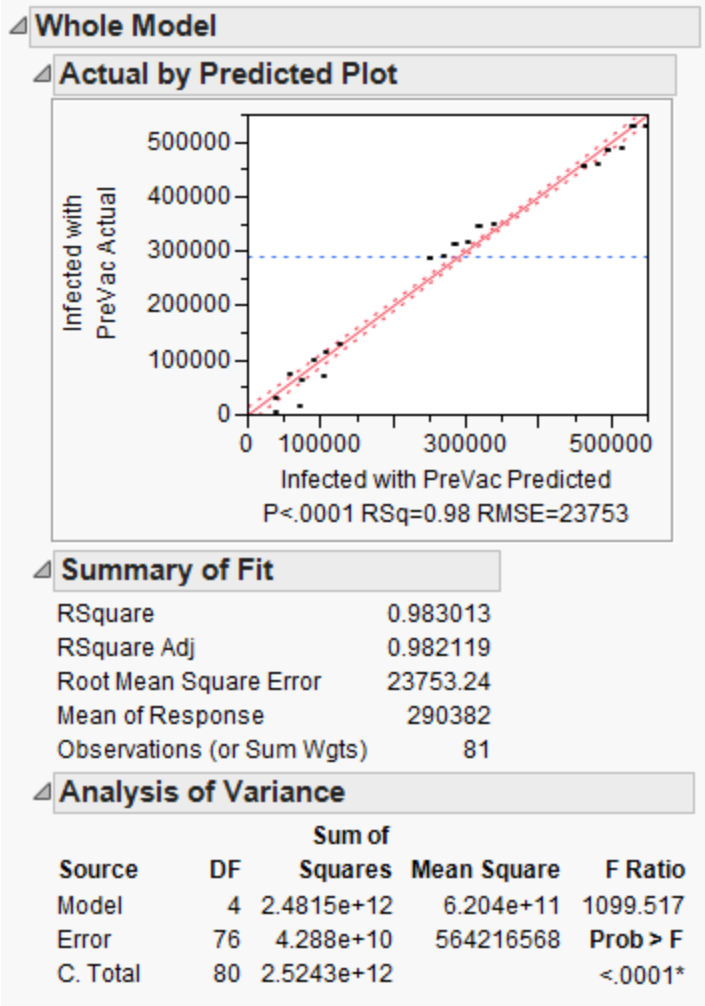


Figure 34. Distribution of Errors from Linear Regression Model for Number Dead

In addition, the results from the 10% Pre-Vaccination Program can also be modeled and analyzed using linear regression and the same variables. Figure 35 displays the linear regression model of the number infected with a 10% Pre-Vaccination Program, while Figure 36 shows the parameter estimates and their significance. The Residual by Predicted Plot in Figure 36 and the quantile plot in Figure 37 are used to confirm that the needed assumptions are met for linear regression.



Summary of Fit

RSquare	0.983013
RSquare Adj	0.982119
Root Mean Square Error	23753.24
Mean of Response	290382
Observations (or Sum Wgts)	81

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	4	2.4815e+12	6.204e+11	1099.517
Error	76	4.288e+10	564216568	Prob > F
C. Total	80	2.5243e+12		<.0001*

Figure 35. Linear Regression Model of Number Infected (with Pre-vaccination)

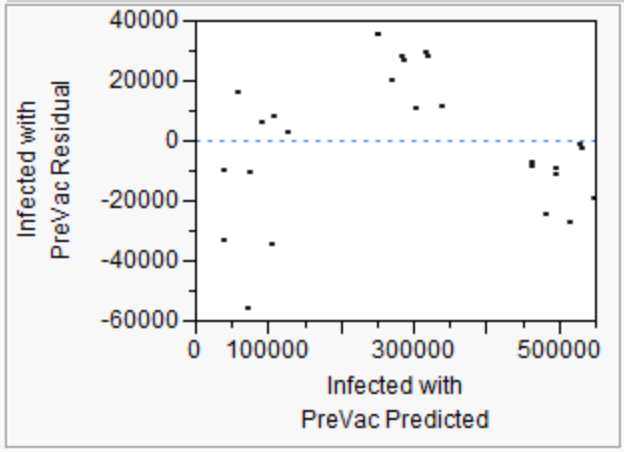
Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|	VIF
Intercept	-250927.1	17141.96	-14.64	<.0001*	.
Stage1	-33552.5	3232.407	-10.38	<.0001*	1
Stage 3	211416.33	3232.407	65.41	<.0001*	1
Death Rate	3.63e-12	32324.07	0.00	1.0000	1
Initial Infected	20.858292	5.904494	3.53	0.0007*	1

Effect Tests

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
Stage1	1	1	6.0792e+10	107.7451	<.0001*
Stage 3	1	1	2.4136e+12	4277.845	<.0001*
Death Rate	1	1	7.1159e-24	0.0000	1.0000
Initial Infected	1	1	7041058831	12.4794	0.0007*

Residual by Predicted Plot



Correlation of Estimates

Corr

	Intercept	Stage1	Stage 3	Death Rate	Initial Infected
Intercept	1.0000	-0.5657	-0.5657	-0.5657	-0.1274
Stage1	-0.5657	1.0000	0.0000	0.0000	0.0000
Stage 3	-0.5657	0.0000	1.0000	0.0000	0.0000
Death Rate	-0.5657	0.0000	0.0000	1.0000	0.0000
Initial Infected	-0.1274	0.0000	0.0000	0.0000	1.0000

Figure 36. Linear Regression Model of Number Infected (with Pre-vaccination) (Parameter Estimates)

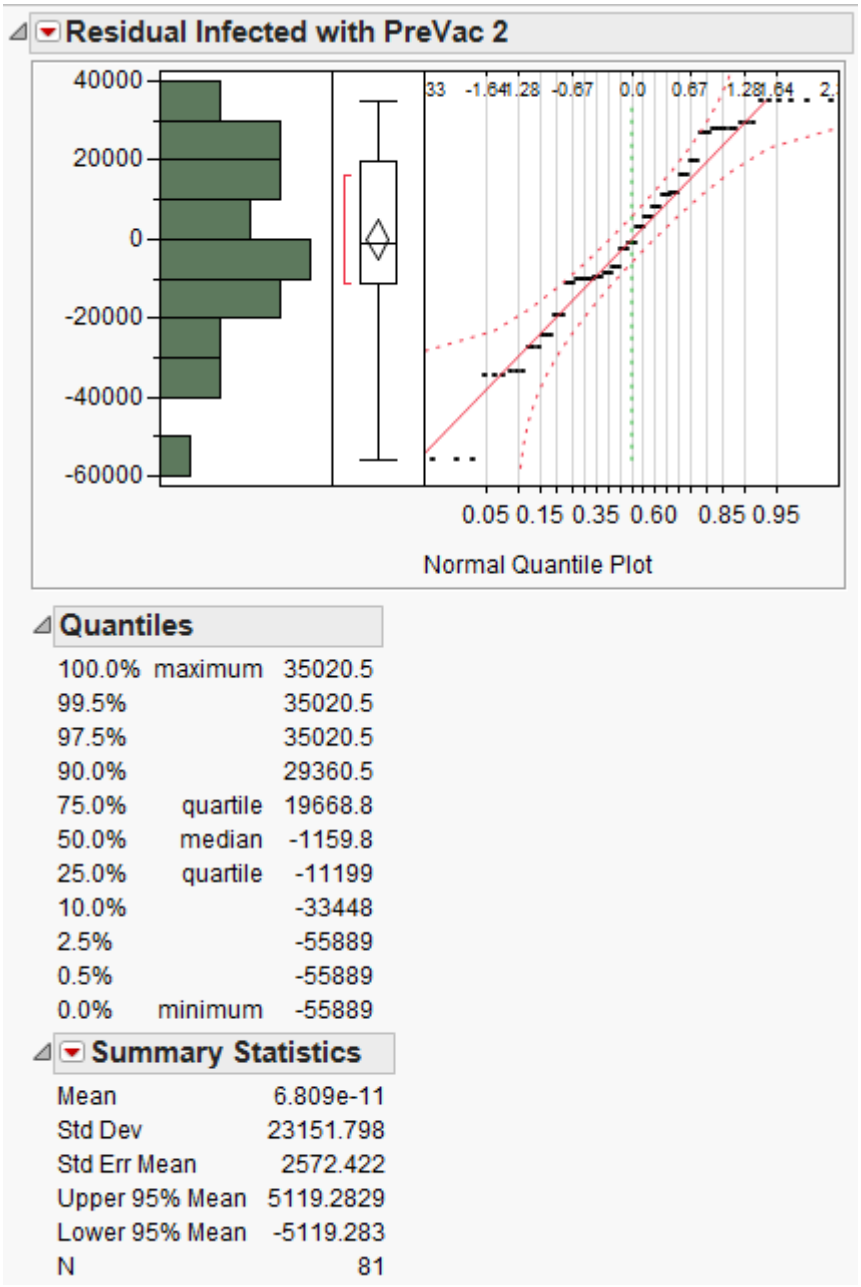


Figure 37. Distribution of Errors from Linear Regression Model for Number Infected (with Pre-vaccination)

Figure 38 displays the linear regression model of the number dead with a 10% Pre-Vaccination Program, while Figure 39 shows the parameter estimates and their significance. The Residual by Predicted Plot in Figure 39 and the quantile plot in Figure 40 are used to confirm that the needed assumptions are met for linear regression.

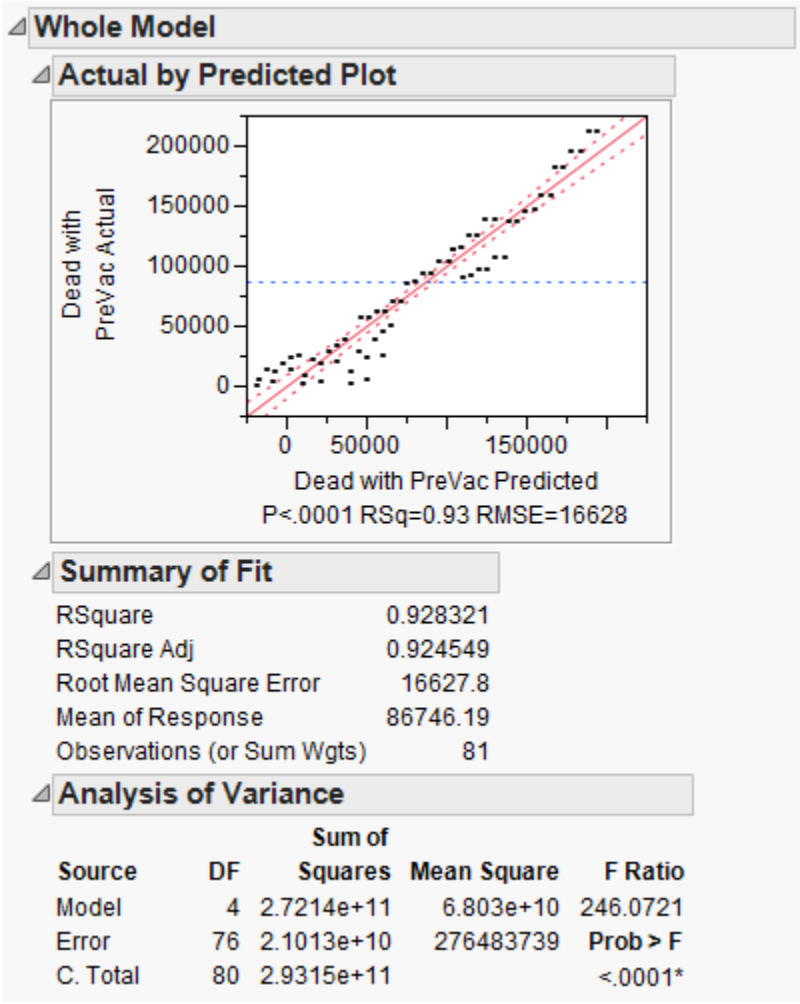
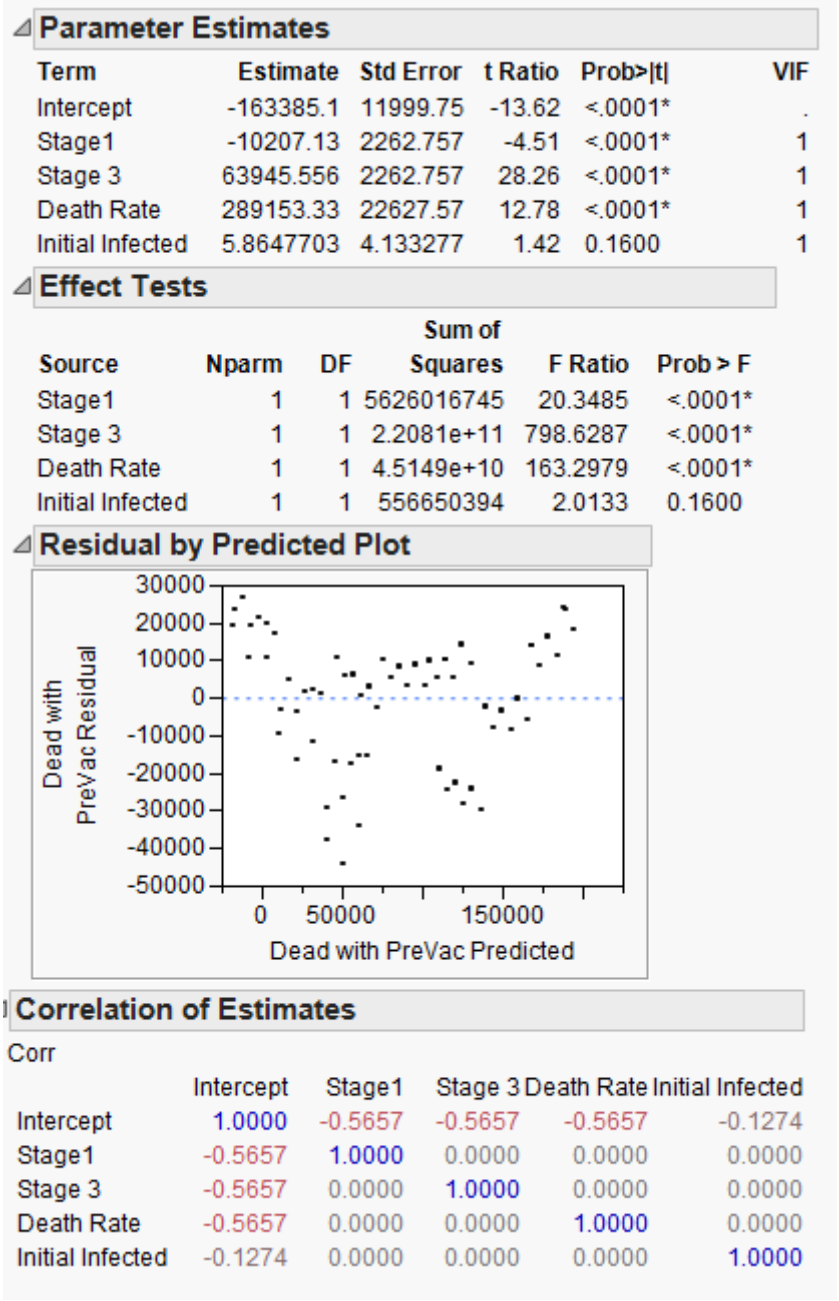


Figure 38. Linear Regression Model of Number Dead (with Pre-vaccination)



Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|	VIF
Intercept	-163385.1	11999.75	-13.62	<.0001*	.
Stage1	-10207.13	2262.757	-4.51	<.0001*	1
Stage 3	63945.556	2262.757	28.26	<.0001*	1
Death Rate	289153.33	22627.57	12.78	<.0001*	1
Initial Infected	5.8647703	4.133277	1.42	0.1600	1

Effect Tests

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
Stage1	1	1	5626016745	20.3485	<.0001*
Stage 3	1	1	2.2081e+11	798.6287	<.0001*
Death Rate	1	1	4.5149e+10	163.2979	<.0001*
Initial Infected	1	1	556650394	2.0133	0.1600

Residual by Predicted Plot

Correlation of Estimates

Corr

	Intercept	Stage1	Stage 3	Death Rate	Initial Infected
Intercept	1.0000	-0.5657	-0.5657	-0.5657	-0.1274
Stage1	-0.5657	1.0000	0.0000	0.0000	0.0000
Stage 3	-0.5657	0.0000	1.0000	0.0000	0.0000
Death Rate	-0.5657	0.0000	0.0000	1.0000	0.0000
Initial Infected	-0.1274	0.0000	0.0000	0.0000	1.0000

Figure 39. Linear Regression Model of Number Dead (with Pre-vaccination) (Parameter Estimates)

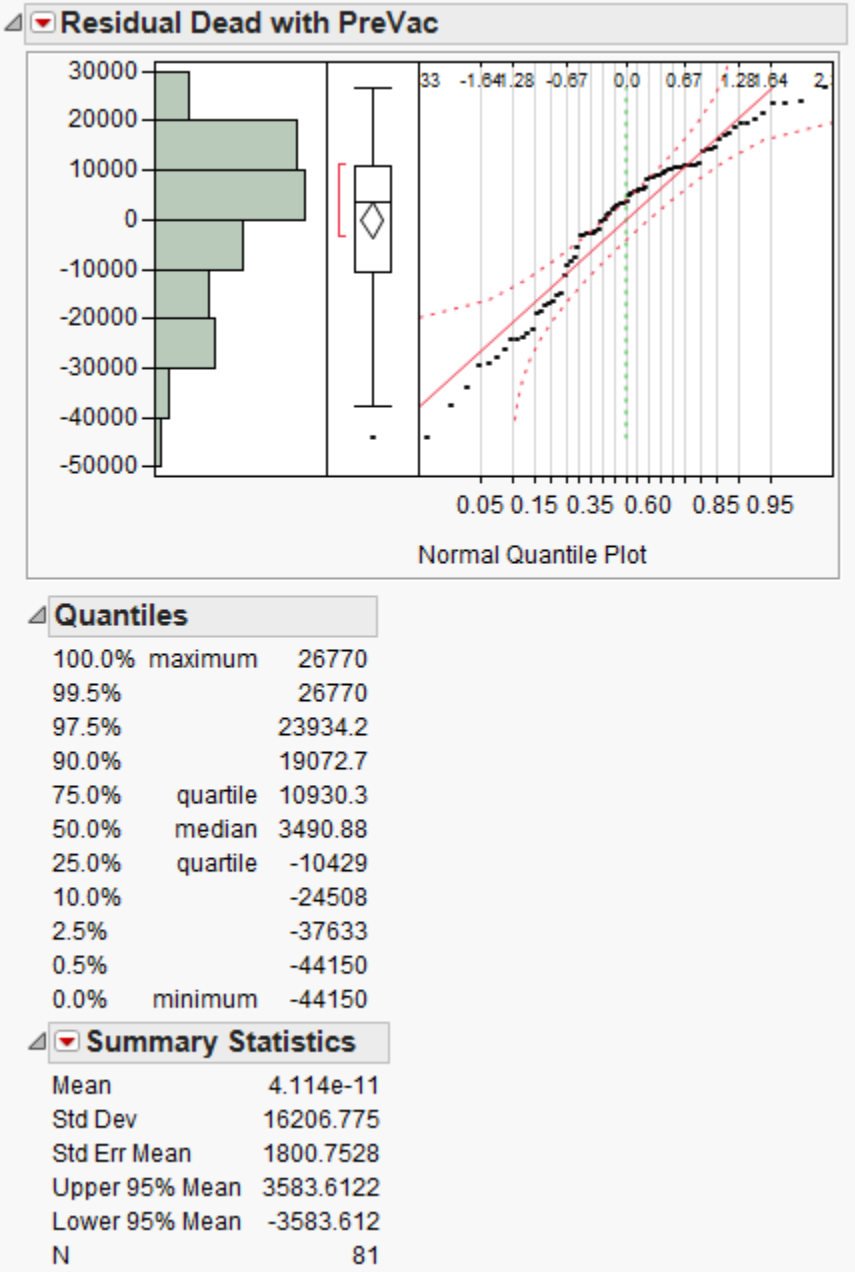


Figure 40. Distribution of Errors from Linear Regression Model for Number Dead (with Pre-vaccination)

Hypothesis Testing of Number Infected with 10% Pre-Vaccination

H_0: No significant difference in the average number of people infected between the normal and 10% pre-vaccinated populations

H_a: A significant difference in the average number of people infected exists between the normal and 10% pre-vaccinated populations

Critical Value: z = 3.27 using α=0.01

Test statistic: $z = \frac{(\overline{x_1}-\overline{x_2})-(\mu_1-\mu_2)}{\sqrt{\frac{\sigma_1^2}{n_1}+\frac{\sigma_2^2}{n_2}}} = \frac{(350642.2-290382)-0}{\sqrt{\frac{442874212}{81}-\frac{564216568}{81}}} = 82.52978$

Conclusion: Reject the null hypothesis, accept the alternative hypothesis. In other words, there is a statistically significant difference between the results.

Hypothesis Testing of Number Dead with 10% Pre-Vaccination

H_0: No significant difference in the average number of people dead between the normal and 10% pre-vaccinated populations

H_a: A significant difference in the average number of people dead exists between the normal and 10% pre-vaccinated populations

Critical Value: z = 3.27 using α=0.01

Test statistic: $z = \frac{(\overline{x_1}-\overline{x_2})-(\mu_1-\mu_2)}{\sqrt{\frac{\sigma_1^2}{n_1}+\frac{\sigma_2^2}{n_2}}} = \frac{(104783.4-86746)-0}{\sqrt{\frac{275971879}{81}-\frac{27648379}{81}}} = 63.20864$

Conclusion: Reject the null hypothesis, accept the alternative hypothesis. In other words, there is a statistically significant difference between the results.

Appendix B: Matlab Code for Kaplan Model

Below is the Matlab code for the Kaplan Model

```
function BioModel7test
clc;

 %The following variables must be determined
Beta1=(10^(-7)/(2*24)); %infection rate
C = 50; %names generated per index
P= .5; %percentage of C who are infected
N = (10^7); %population size
R1 = 1/(2*24*3); %disease stage 1 rate
R2 = 1/(2*24*8); %disease stage 2 rate
R3 = 1/(2*24*3); %disease stage 3 rate
R4 = 1/(2*24*12); %disease stage 4 rate
NV = 5000; %number of vaccinators
Mu1 = 50/(2*24); %Service Rate
H1 = .9; %fraction febrile in stage 3
Alpha1 = 1/(2*24*5); %quarantine rate
VZero = 0.975; %vaccine efficacy at stage 0
V1 = 0.975; %vaccine efficacy at stage 1
Delta1 = 0.3; %small pox death rate
F1 = 10^(-6); %vaccination fatality rate
I1Zero = 10^3; %initial number infected
I2Zero=0;
I3Zero=0;
I4Zero=0;
QZero=0;
Q1=0;
Q2=0;
Q3=0;
S1=0;
D=0; %number dead
H2 = 0; %number immune
D=0;
Z=0;
Tau1=5;
InitialRZero=Beta1*N/R3;
VRate=0.5; %percent vaccinated
PreVac=VRate*N;
%------------------------
SZero=N-I1Zero-I3Zero-PreVac;
I1One=0;
I2One=0;
I3One=0;
I4One=0;
I4=0;
I3=I3Zero+Q3+I3One;

Svalue=SZero+QZero;

for Time = 1:1:5*24*2
```

```
RZero=Beta1*(SZero+QZero+S1)/R3;
Kappa1=((C-P*RZero)*(R3*I3))/N;
Lambda1=((Beta1*SZero)/(R3+Kappa1))*((R3+Kappa1)/(R1+R3+Kappa1));
Lambda2=(R1/(R1+R3+Kappa1))*((R3+Kappa1)/(R2+R3+Kappa1))*((Beta1*SZero)
/(R3+Kappa1));
Lambda3=(R1/(R1+R3+Kappa1))*(R2/(R2+R3+Kappa1))*((R3+Kappa1)/(R3+R3+Kap
pa1))*((Beta1*SZero)/(R3+Kappa1));

SZeroChange=(-Beta1*I3*SZero)-(((C-P*RZero)*(SZero/N))*R3*I3);
I1ZeroChange=(Beta1*I3*SZero)-((((C-
P*RZero)*(I1Zero/N))+(P*Lambda1))*R3*I3)-(R1*I1Zero);
I2ZeroChange=(R1*I1Zero)-((((C-
P*RZero)*(I2Zero/N))+(P*Lambda2))*R3*I3)-(R2*I2Zero);
I3ZeroChange=(R2*I2Zero)-((((C-
P*RZero)*(I3Zero/N))+(P*Lambda3))*R3*I3)-(R3*I3Zero);
I4ZeroChange=(R3*I3Zero)-(R4*I4Zero);

QTotal=QZero+Q1+Q2+Q3;

H2Change=(1-F1)*H1*(Q3*min(1, Mu1*NV/QTotal))-(R3*H2)-(Alpha1*H2);
ZChange=((1-F1)*((VZero*QZero)+(V1*Q1))*min(1, Mu1*NV/QTotal))+((1-
Delta1)*R4*(I4Zero+I4One));
DChange=(F1*min(1, Mu1 *NV/QTotal))+(Delta1*R4*(I4Zero+I4One));

SZero=SZero+SZeroChange;
I1Zero=I1Zero+I1ZeroChange;
I2Zero=I2Zero+I2ZeroChange;
I3Zero=I3Zero+I3ZeroChange;
I4Zero=I4Zero+I4ZeroChange;

Q=QZero+Q1+Q2+Q3;
Z=Z+ZChange;
D=D+DChange;
H2=H2+H2Change;
ITotal=I1Zero+I2Zero+I3Zero+I4Zero+I1One+I2One+I3One+I4One;
t=Time;
DataMatrix2(t,1)=I1Zero;
DataMatrix2(t,2)=I2Zero;
DataMatrix2(t,3)=I3Zero;
DataMatrix2(t,4)=I4Zero;
DataMatrix2(t,5)=H2;
DataMatrix2(t,6)=Q;
DataMatrix2(t,7)=ITotal;
DataMatrix2(t,8)=D;

I3=I3Zero+Q3+I3One;

Svalue=SZero+QZero;

end

for Time = 5*24*2:1:350*24*2
```

```
disp(Time)

RZero=Beta1*(SZero+QZero+S1)/R3;
Kappa1=((C-P*RZero)*(R3*I3))/N;
Lambda1=((Beta1*SZero)/(R3+Kappa1))*((R3+Kappa1)/(R1+R3+Kappa1));
Lambda2=(R1/(R1+R3+Kappa1))*((R3+Kappa1)/(R2+R3+Kappa1))*((Beta1*SZero)
/(R3+Kappa1));
Lambda3=(R1/(R1+R3+Kappa1))*(R2/(R2+R3+Kappa1))*((R3+Kappa1)/(R3+R3+Kap
pa1))*((Beta1*SZero)/(R3+Kappa1));
SZeroChange=(-Beta1*I3*SZero)-(((C-P*RZero)*(SZero/N))*R3*I3);
I1ZeroChange=(Beta1*I3*SZero)-((((C-
P*RZero)*(I1Zero/N))+(P*Lambda1))*R3*I3)-(R1*I1Zero);
I2ZeroChange=(R1*I1Zero)-((((C-
P*RZero)*(I2Zero/N))+(P*Lambda2))*R3*I3)-(R2*I2Zero);
I3ZeroChange=(R2*I2Zero)-((((C-
P*RZero)*(I3Zero/N))+(P*Lambda3))*R3*I3)-(R3*I3Zero);
I4ZeroChange=(R3*I3Zero)-(R4*I4Zero);

QTotal=QZero+Q1+Q2+Q3;
QZeroChange=((C-P*RZero)*(SZero/N)*R3*I3)-(Beta1*I3*QZero)-
(QZero*min(1,Mu1*NV/QTotal));
Q1Change=(Beta1*I3*QZero)+((((C-
P*RZero)*(I1Zero/N))+(P*Lambda1))*R3*I3)-(Q1*min(1,Mu1*NV/QTotal))-
(R1*Q1);
Q2Change=(R1*Q1)+((((C-P*RZero)*(I2Zero/N))+(P*Lambda2))*R3*I3)-
(Q2*min(1,Mu1*NV/QTotal))-(R2*Q2);
Q3Change=(R2*Q2)+((((C-P*RZero)*(I3Zero/N))+(P*Lambda3))*R3*I3)-
(Q3*min(1, Mu1*NV/QTotal))-(R3*Q3);

S1Change=((1-F1)*(1-VZero)*QZero*min(1,Mu1*NV/QTotal))-(Beta1*S1*I3);
I1OneChange=(Beta1*I3*S1)+((1-F1)*(1-V1)*Q1*min(1,Mu1*NV/QTotal))-
(R1*I1One);
I2OneChange=(R1*I1One)+((1-F1)*Q2*min(1, Mu1*NV/QTotal))-(R2*I2One);
I3OneChange=(R2*I2One)+((1-F1)*(1-H1)*Q3*min(1,
Mu1*NV/QTotal))+(Alpha1*H2)-(R3*I3One);
I4OneChange=(R3*(I3One+Q3+H2))-(R4*I4One);

H2Change=(1-F1)*H1*(Q3*min(1, Mu1*NV/QTotal))-(R3*H2)-(Alpha1*H2);
ZChange=((1-F1)*((VZero*QZero)+(V1*Q1))*min(1, Mu1*NV/QTotal))+((1-
Delta1)*R4*(I4Zero+I4One));
DChange=(F1*min(1, Mu1 *NV/QTotal))+(Delta1*R4*(I4Zero+I4One));

SZero=SZero+SZeroChange;
S1=S1+S1Change;
I1Zero=I1Zero+I1ZeroChange;
I2Zero=I2Zero+I2ZeroChange;
I3Zero=I3Zero+I3ZeroChange;
I4Zero=I4Zero+I4ZeroChange;
I1One=I1One+I1OneChange;
I2One=I2One+I2OneChange;
I3One=I3One+I3OneChange;
I4One=I4One+I4OneChange;
QZero=QZero+QZeroChange;
Q1=Q1+Q1Change;
```

```
Q2=Q2+Q2Change;
Q3=Q3+Q3Change;
Q=QZero+Q1+Q2+Q3;
Z=Z+ZChange;
D=D+DChange;
H2=H2+H2Change;
ITotal=I1Zero+I2Zero+I3Zero+I4Zero+I1One+I2One+I3One+I4One;
t=Time;
DataMatrix2(t,1)=Q1;
DataMatrix2(t,2)=Q2;
DataMatrix2(t,3)=Q3;
DataMatrix2(t,4)=Q1+Q2+Q3;
DataMatrix2(t,5)=H2;
DataMatrix2(t,6)=Q;
DataMatrix2(t,7)=ITotal;
DataMatrix2(t,8)=D;
%DataMatrix2(t,2)=Q;
I3=I3Zero+Q3+I3One;

Svalue=SZero+QZero;

end

%disp(RZero)
disp(DataMatrix2(:,6))
disp(DataMatrix2(:,7))
plot((DataMatrix2(:,7)))

for Time2=1:1:350*2
    DataMatrix3(Time2,1:8)=DataMatrix2(Time2*24,1:8);
end

T1=((1/R1)/(2*24));
T2=(((1/R2)/(2*24))+(1/R1)/(2*24));
T3=(((1/R3)/(2*24))+((1/R2)/(2*24))+(1/R1)/(2*24));
T4=(((1/R4)/(2*24))+((1/R3)/(2*24))+((1/R2)/(2*24))+(1/R1)/(2*24));
StageTime=T1+T2+T3+T4;

ISum=sum(DataMatrix3(:,7))/2;
Q1Die=sum(DataMatrix3(:,1))*(10^(-6))*T1/2;
Q2Die=sum(DataMatrix3(:,2))*(10^(-6))*T2/2;
Q3Die=sum(DataMatrix3(:,3))*(10^(-6))*T3/2;
Q1Save=sum(DataMatrix3(:,1))*.975*T1/2;
IFull=(ISum-Q1Die-Q2Die-Q3Die-Q1Save)/(StageTime);
NumInf=IFull+(Q1Die/T1)+(Q2Die/T2)+(Q3Die/T3)+(Q1Save/T1);


end
```

Appendix C: Airline Flight Itineraries Codes

Below is the Matlab code for establishing the whole airline network

```
[m,n] = size(DataMod3);
%[p,q] = size(Port);

K = 1;
NewMatrix=zeros(m,7);

for i=1:1:m
    if i<m

    if DataMod3(i,4)==DataMod3(i+1,4) && DataMod3(i,5)==DataMod3(i+1,5)
        TotalPassenger=DataMod3(i,1);
        TotalFlight=DataMod3(i,7);
        j=i+1;
        Last=0;
        if j>m
                Last=1;
            end
        while Last ==0 && DataMod3(j,4)==DataMod3(i,4) &&
DataMod3(j,5)==DataMod3(i,5)
            TotalPassenger=TotalPassenger+DataMod3(j,1);
            TotalFlight=TotalFlight+DataMod3(j,7);
            j=j+1;
            if j>m
                Last=1;
            end
        end
    else
        TotalPassenger=DataMod3(i,1);
        TotalFlight=DataMod3(i,7);
    end
    end
%     if i==m-1
%         TotalPassenger=DataMod3(i,1)+DataMod3(i+1,1);
%     end

    if i==1
    NewMatrix(K,1)=TotalPassenger;
    NewMatrix(K,2)=DataMod3(i,2);
    NewMatrix(K,3)= 0;
    NewMatrix(K,4)=DataMod3(i,4);
    NewMatrix(K,5)=DataMod3(i,5);
    NewMatrix(K,6)=DataMod3(i,6);
    NewMatrix(K,7)=TotalFlight;
    K=K+1;
    else if DataMod3(i,4)~=NewMatrix(K-1,4)||
DataMod3(i,5)~=NewMatrix(K-1,5)
    NewMatrix(K,1)=TotalPassenger;
    NewMatrix(K,2)=DataMod3(i,2);
    NewMatrix(K,3)= 0;
```

```
    NewMatrix(K,4)=DataMod3(i,4);
    NewMatrix(K,5)=DataMod3(i,5);
    NewMatrix(K,6)=DataMod3(i,6);
    NewMatrix(K,7)=TotalFlight;
    K=K+1;
    end

    TotalPassenger=0;
end
end

NetworkF=zeros(p+1,p+1);
NetworkF(2:p+1,1)=Port(:,1);
NetworkF(1,2:p+1)=Port(:,1)';

for g=2:1:p+1
    for h=2:1:p+1
        for f=1:1:8000
        if NetworkF(g,1)==NewMatrix(f,4) &&
NetworkF(1,h)==NewMatrix(f,5)
            NetworkF(g,h)=NewMatrix(f,7);
        end
        end
    end
end
```

Below is the Matlab code for building the network for a specific airline

```
[m,n] = size(DataModE);
%[p,q] = size(Port);

K = 1;
NewMatrix2=zeros(m,6);

for i=1:1:m
    if i<m %&& DataModE(i,3)==19393

    if DataModE(i,4)==DataModE(i+1,4) &&
DataModE(i,5)==DataModE(i+1,5)% && DataModE(i,3)==DataModE(i+1,3)
        TotalPassenger=DataModE(i,1);
        %TotalFlight=DataMod3(i,7);
        j=i+1;
        Last=0;
        if j>m
                Last=1;
            end
        while Last ==0 && DataModE(j,4)==DataModE(i,4) &&
DataModE(j,5)==DataModE(i,5)
            TotalPassenger=TotalPassenger+DataModE(j,1);
           % TotalFlight=TotalFlight+DataMod3(j,7);
            j=j+1;
            if j>m
```

```
                Last=1;
            end
        end
    else
        TotalPassenger=DataModE(i,1);
        %TotalFlight=DataMod3(i,7);
    end
    end
    if i==m %&& DataModE(i,3)==19393
        TotalPassenger=DataModE(i,1);%+DataModE(i+1,1);
    end
    %if DataModE(i,3)==19393
        if K==1
            NewMatrix2(K,1)=TotalPassenger;
            NewMatrix2(K,2)=DataModE(i,2);
            NewMatrix2(K,3)=DataModE(i,3);
            NewMatrix2(K,4)=DataModE(i,4);
            NewMatrix2(K,5)=DataModE(i,5);
            NewMatrix2(K,6)=DataModE(i,6);
            %NewMatrix2(K,7)=TotalFlight;
            K=K+1;

        else if  DataModE(i,4)~=NewMatrix2(K-1,4)||
DataModE(i,5)~=NewMatrix2(K-1,5)

                NewMatrix2(K,1)=TotalPassenger;
                NewMatrix2(K,2)=DataModE(i,2);
                NewMatrix2(K,3)=DataModE(i,3);
                NewMatrix2(K,4)=DataModE(i,4);
                NewMatrix2(K,5)=DataModE(i,5);
                NewMatrix2(K,6)=DataModE(i,6);
                %NewMatrix2(K,7)=TotalFlight;
                K=K+1;

         end
        %end
    end
    TotalPassenger=0;
end

disp(NewMatrix2);


%-----------------------------------------------------
% [p,q] = size(Port);
NetworkE=zeros(p+1,p+1);
NetworkE(2:p+1,1)=Port(:,1);
NetworkE(1,2:p+1)=Port(:,1)';

for g=2:1:p+1
    for h=2:1:p+1
        for f=1:1:m
        if NetworkE(g,1)==NewMatrix2(f,4) &&
NetworkE(1,h)==NewMatrix2(f,5)
```

```
            %NetworkE(g,h)=round(NewMatrix2(f,1)/NewMatrix2(f,7));
            NetworkE(g,h)=NewMatrix2(f,1);
        end
        end
    end
end
```

Matlab code for finding the optimal four flight itinerary

```
InfectMatrix=zeros(p+1,p+2);
InfectMatrix(2:p+1,1)=Port(:,1);
InfectMatrix(1,2:p+1)=Port(:,1)';

Network1=zeros(p+9,p+9);
Network1(2:p+1,1)=Port(:,1);
Network1(1,2:p+1)=Port(:,1)';
Network1(1:p+1,1:p+1)=NetworkE(:,:);

% for d=2:1:p+1
%     for f=2:1:p+1
%         if NetworkF(d,f)<30
%             Network1(d,f)=0;
%         end
%     end
% end
Network1(2:p+9,p+2:p+9)=ones(p+8,8);
Network2=zeros(p+9,p+9);
Network2(2:p+1,1)=Port(:,1);
Network2(1,2:p+1)=Port(:,1)';
for g=2:1:p+1
    for h=2:1:p+1
        if NetworkDistanceGroup(g,h)>0
            Network2(g,h)=NetworkDistanceGroup(g,h)+1;
        end
    end
end
Connect=0;
Dis1=0;
Dis2=0;
Dis3=0;
TotalDis=0;
Distance=0;

K1=1;
K2=1;
K3=1;
K4=1;
% K5=1;
% K6=6;
Posf1=zeros(p+8,1);
Posf2=zeros(p+8,1);
Posf3=zeros(p+8,1);
Posf4=zeros(p+8,1);
% Posf5=zeros(p+8,1);
```

```
% Posf6=zeros(p+8,1);

%BackupNetwork1E(:,:)=Network1(:,:);

LAXSFAno=0;

if LAXSFAno==1;
   Network1(576,368)=0;
   Network1(368,576)=0;
end

DALHOUno=1;

if DALHOUno==1;
   Network1(158,278)=0;
   Network1(278,158)=0;
end

BioDetect=0;

if BioDetect==1

Network1(496,:)=0;
Network1(:,496)=0;
Network1(378,:)=0;
Network1(:,378)=0;
Network1(322,:)=0;
Network1(:,322)=0;
Network1(161,:)=0;
Network1(:,161)=0;
Network1(291,:)=0;
Network1(:,291)=0;
Network1(87,:)=0;
Network1(:,87)=0;
Network1(407,:)=0;
Network1(:,407)=0;
Network1(476,:)=0;
Network1(:,476)=0;
Network1(576,:)=0;
Network1(:,576)=0;
Network1(48,:)=0;
Network1(:,48)=0;
Network1(610,:)=0;
Network1(:,610)=0;
Network1(278,:)=0;
Network1(:,278)=0;
Network1(293,:)=0;
Network1(:,293)=0;
Network1(368,:)=0;
Network1(:,368)=0;
Network1(559,:)=0;
Network1(:,559)=0;
end
```

```
for Start=1:1:p
    disp(Start);
   % if Start<15

    for i1=1:1:p
        if Network1(Start+1,i1+1)>0
            Posf1(K1,1)=i1;
            K1=K1+1;
        end
    end

    for Flight1=1:1:K1-1

        for i2=1:1:p+1
            if Network1(Posf1(Flight1,1)+1,i2+1)>0
                Posf2(K2,1)=i2;
                K2=K2+1;
            end
        end

        for Flight2=1:1:K2-1
            %disp(Flight2)
              for i3=1:1:p+2
                 if Network1(Posf2(Flight2,1)+1,i3+1)>0
                     Posf3(K3,1)=i3;
                    K3=K3+1;
                 end
              end

            for Flight3=1:1:K3-1

                for i4=1:1:p+3
                 if Network1(Posf3(Flight3,1)+1,i4+1)>0
                     Posf4(K4,1)=i4;
                    K4=K4+1;
                 end
                end

                for Flight4=1:1:K4-1
%                       for i5=1:1:p+4
%                          if Network1(Posf4(Flight4,1)+1,i5+1)>0
%                           Posf5(K5,1)=i5;
%                          K5=K5+1;
%                          end
%                       end
%                     for Flight5=1:1:K5-1
%                         for i6=1:1:p+5
%                          if Network1(Posf5(Flight5,1)+1,i6+1)>0
%                           Posf6(K6,1)=i6;
%                             K6=K6+1;
%                          end
```

```
%                           end
%                           for Flight6=1:1:K6-1

Connect=0;
TotalDis=0;
Distance=0;
Cycle=0;
TotalGain=0;
%   if Network1(Start+1,Flight1+1)>0
%   if Network1(Flight1+1, Flight2+1)>0
%       if Network1(Flight2+1, Flight3+1)>0
%           if Network1(Flight3+1, Flight4+1)>0
%
%           end
%       end
%   end
%   end
  Dis1= Network2(Start+1,Posf1(Flight1,1)+1)+
Network2(Posf1(Flight1,1)+1,Posf2(Flight2,1)+1)+Network2(Posf2(Flight2,
1)+1,Posf3(Flight3,1)+1)+Network2(Posf3(Flight3,1)+1,Posf4(Flight4,1)+1
);
  %Dis2=
Network2(Posf4(Flight4,1)+1,Posf5(Flight5,1)+1)+Network2(Posf5(Flight5,
1)+1,Posf6(Flight6,1)+1);
  TotalDis=Dis1+Dis2;

  if TotalDis<19
      Distance=1;
  end

  if Network2(Start+1,Posf2(Flight2,1)+1)==0 || Posf2(Flight2,1)+1>699
||
(Network2(Start+1,Posf2(Flight2,1)+1)+3)>(Network2(Start+1,Posf1(Flight
1,1)+1)+ Network2(Posf1(Flight1,1)+1,Posf2(Flight2,1)+1))
      if Network2(Start+1,Posf3(Flight3,1)+1)==0 ||
Posf3(Flight3,1)+1>699 ||
(Network2(Start+1,Posf3(Flight3,1)+1)+4)>(Network2(Start+1,Posf1(Flight
1,1)+1)+ Network2(Posf1(Flight1,1)+1,Posf2(Flight2,1)+1)+
Network2(Posf2(Flight2,1)+1,Posf3(Flight3,1)+1))
          if Network2(Start+1,Posf4(Flight4,1)+1)==0 ||
Posf4(Flight4,1)+1>699 ||
(Network2(Start+1,Posf4(Flight4,1)+1)+4)>(Network2(Start+1,Posf1(Flight
1,1)+1)+ Network2(Posf1(Flight1,1)+1,Posf2(Flight2,1)+1)+
Network2(Posf2(Flight2,1)+1,Posf3(Flight3,1)+1)+Network2(Posf3(Flight3,
1)+1,Posf4(Flight4,1)+1))
              if Network2(Posf1(Flight1,1)+1,Posf3(Flight3,1)+1)==0 ||
Posf3(Flight3,1)+1>699 ||
(Network2(Posf1(Flight1,1)+1,Posf3(Flight3,1)+1)+3)>(Network2(Posf1(Fli
ght1,1)+1,Posf2(Flight2,1)+1)+Network2(Posf2(Flight2,1)+1,Posf3(Flight3
,1)+1))
                  if Network2(Posf1(Flight1,1)+1,Posf4(Flight4,1)+1)==0
|| Posf4(Flight4,1)+1>699 ||
(Network2(Posf1(Flight1,1)+1,Posf4(Flight4,1)+1)+4)>
(Network2(Posf1(Flight1,1)+1,Posf2(Flight2,1)+1)+Network2(Posf2(Flight2
```

```
,1)+1,Posf3(Flight3,1)+1)+Network2(Posf3(Flight3,1)+1,Posf4(Flight4,1)+
1))
                        if
Network2(Posf2(Flight2,1)+1,Posf4(Flight4,1)+1)==0 ||
Posf4(Flight4,1)+1>699 ||
(Network2(Posf2(Flight2,1)+1,Posf4(Flight4,1)+1)+3)>(Network2(Posf2(Fli
ght2,1)+1,Posf3(Flight3,1)+1)+Network2(Posf3(Flight3,1)+1,Posf4(Flight4
,1)+1))
                            Connect=1;
                        end
                    end
                end
            end
        end
    end

    if Start~=Posf2(Flight2,1) && Start~=Posf3(Flight3,1) &&
Start~=Posf4(Flight4,1)% && Start~=Posf5(Flight5,1) &&
Start~=Posf6(Flight6,1)
            if Posf1(Flight1,1)~=Posf3(Flight3,1) &&
Posf1(Flight1,1)~=Posf4(Flight4,1) %&&
Posf1(Flight1,1)~=Posf5(Flight5,1) &&
Posf1(Flight1,1)~=Posf6(Flight6,1)
                if Posf2(Flight2,1)~=Posf4(Flight4,1) %&&
Posf2(Flight1,1)~=Posf5(Flight5,1) &&
Posf2(Flight1,1)~=Posf6(Flight6,1)
                    %if Posf3(Flight3,1)~=Posf5(Flight5,1) &&
Posf3(Flight3,1)~=Posf6(Flight6,1)
                        %if Posf4(Flight4,1)~=Posf6(Flight6,1)


                                                    Cycle=1;


                        % end
                    %end
                    end

            end

        end


    if Cycle==1 && Distance==1 && Connect==1
    Gain1= Network1(Start+1,Posf1(Flight1,1)+1)+
Network1(Posf1(Flight1,1)+1,Posf2(Flight2,1)+1)+Network1(Posf2(Flight2,
1)+1,Posf3(Flight3,1)+1)+Network1(Posf3(Flight3,1)+1,Posf4(Flight4,1)+1
);
     % Gain2=
Network1(Posf4(Flight4,1)+1,Posf5(Flight5,1)+1)+Network1(Posf5(Flight5,
1)+1,Posf4(Flight6,1)+1);
    TotalGain=Gain1+Gain2;
```

```
  if TotalGain>InfectMatrix(Start+1,p+2)
      InfectMatrix(Start+1,2:p+2)=0;
      InfectMatrix(Start+1,Posf1(Flight1,1)+1)=1;
      InfectMatrix(Start+1,Posf2(Flight2,1)+1)=2;
      InfectMatrix(Start+1,Posf3(Flight3,1)+1)=3;
      InfectMatrix(Start+1,Posf4(Flight4,1)+1)=4;
     % InfectMatrix(Start+1,Posf5(Flight5,1)+1)=1;
     % InfectMatrix(Start+1,Posf6(Flight6,1)+1)=1;
      InfectMatrix(Start+1,p+2)=TotalGain;
  end
  end
  Gain1=0;
  Gain2=0;
  Dis1=0;
  Dis2=0;
%                           end
%                           K6=1;
%                           Posf6=zeros(p+8,1);
%                       end
%                       K5=1;
%                       Posf5=zeros(p+8,1);
                  end
                  K4=1;
                  Posf4=zeros(p+8,1);
              end
              K3=1;
              Posf3=zeros(p+8,1);
          end
          K2=1;
          Posf2=zeros(p+8,1);
    end
    %disp(Start);
    K1=1;
    Posf1=zeros(p+8,1);
    %end
end

MaxMatrix=zeros(p,2);
MaxMatrix(:,1)=InfectMatrix(2:p+1,1);
MaxMatrix(:,2)=InfectMatrix(2:p+1,p+2);

InterestMatrix=zeros(p+1,10);
Best=[404
463
100
7
549
158
588
195
48
596
];
```

```
for g=1:1:10
InterestMatrix(:,g)=InfectMatrix(Best(g,1),1:p+1)';
end
```

Matlab code for optimizing the two flight itinerary at international airports

```
InfectMatrix=zeros(p+1,p+2);
InfectMatrix(2:p+1,1)=Port(:,1);
InfectMatrix(1,2:p+1)=Port(:,1)';

Network1=zeros(p+9,p+9);
Network1(2:p+1,1)=Port(:,1);
Network1(1,2:p+1)=Port(:,1)';
Network1(1:p+1,1:p+1)=NetworkT(:,:);

% for d=2:1:p+1
%     for f=2:1:p+1
%         if NetworkF(d,f)<30
%             Network1(d,f)=0;
%         end
%     end
% end
Network1(2:p+9,p+2:p+9)=ones(p+8,8);
Network2=zeros(p+9,p+9);
Network2(2:p+1,1)=Port(:,1);
Network2(1,2:p+1)=Port(:,1)';
for g=2:1:p+1
    for h=2:1:p+1
        if NetworkDistanceGroup(g,h)>0
            Network2(g,h)=NetworkDistanceGroup(g,h)+1;
        end
    end
end
Connect=0;
Dis1=0;
Dis2=0;
Dis3=0;
TotalDis=0;
Distance=0;

K1=1;
K2=1;
K3=1;
K4=1;
% K5=1;
% K6=6;
Posf1=zeros(p+8,1);
Posf2=zeros(p+8,1);
```

```
Posf3=zeros(p+8,1);
Posf4=zeros(p+8,1);
% Posf5=zeros(p+8,1);
% Posf6=zeros(p+8,1);

%BackupNetwork1E(:,:)=Network1(:,:);

LAXSFAno=1;

if LAXSFAno==1;
   Network1(576,368)=0;
   Network1(368,576)=0;
end

BioDetect=1;

if BioDetect==1

Network1(496,:)=0;
Network1(:,496)=0;
Network1(378,:)=0;
Network1(:,378)=0;
Network1(322,:)=0;
Network1(:,322)=0;
Network1(161,:)=0;
Network1(:,161)=0;
Network1(291,:)=0;
Network1(:,291)=0;
Network1(87,:)=0;
Network1(:,87)=0;
Network1(407,:)=0;
Network1(:,407)=0;
Network1(476,:)=0;
Network1(:,476)=0;
Network1(576,:)=0;
Network1(:,576)=0;
Network1(48,:)=0;
Network1(:,48)=0;
Network1(610,:)=0;
Network1(:,610)=0;
Network1(278,:)=0;
Network1(:,278)=0;
Network1(293,:)=0;
Network1(:,293)=0;
Network1(368,:)=0;
Network1(:,368)=0;
Network1(559,:)=0;
Network1(:,559)=0;
end

V=1;

MaxLocation1=zeros(8000,3);
```

```
MaxLocation2=zeros(8000,3);
MaxLocation3=zeros(8000,3);
MaxLocation4=zeros(8000,3);
MaxLocation5=zeros(8000,3);
MaxLocation6=zeros(8000,3);
MaxLocation7=zeros(8000,3);
MaxLocation8=zeros(8000,3);
MaxLocation9=zeros(8000,3);
MaxLocation10=zeros(8000,3);


for Start=1:1:p
    disp(Start);


    for i1=1:1:p
        if Network1(Start+1,i1+1)>0
            Posf1(K1,1)=i1;
            K1=K1+1;
        end
    end

    for Flight1=1:1:K1-1

        for i2=1:1:p+1
            if Network1(Posf1(Flight1,1)+1,i2+1)>0
                Posf2(K2,1)=i2;
                K2=K2+1;
            end
        end

        for Flight2=1:1:K2-1



Connect=0;
TotalDis=0;
Distance=0;
Cycle=0;
TotalGain=0;

  Dis1= Network2(Start+1,Posf1(Flight1,1)+1)+
Network2(Posf1(Flight1,1)+1,Posf2(Flight2,1)+1);

  TotalDis=Dis1;

  if TotalDis<19
      Distance=1;
  end

  if Network2(Start+1,Posf2(Flight2,1)+1)==0 || Posf2(Flight2,1)+1>699
||
```

```
(Network2(Start+1,Posf2(Flight2,1)+1)+3)>(Network2(Start+1,Posf1(Flight
1,1)+1)+ Network2(Posf1(Flight1,1)+1,Posf2(Flight2,1)+1))
%       if Network2(Start+1,Posf3(Flight3,1)+1)==0 ||
Posf3(Flight3,1)+1>699 ||
(Network2(Start+1,Posf3(Flight3,1)+1)+3)>(Network2(Start+1,Posf1(Flight
1,1)+1)+ Network2(Posf1(Flight1,1)+1,Posf2(Flight2,1)+1)+
Network2(Posf2(Flight2,1)+1,Posf3(Flight3,1)+1))
%           if Network2(Start+1,Posf4(Flight4,1)+1)==0 ||
Posf4(Flight4,1)+1>699 ||
(Network2(Start+1,Posf4(Flight4,1)+1)+3)>(Network2(Start+1,Posf1(Flight
1,1)+1)+ Network2(Posf1(Flight1,1)+1,Posf2(Flight2,1)+1)+
Network2(Posf2(Flight2,1)+1,Posf3(Flight3,1)+1)+Network2(Posf3(Flight3,
1)+1,Posf4(Flight4,1)+1))
%               if Network2(Posf1(Flight1,1)+1,Posf3(Flight3,1)+1)==0
|| Posf3(Flight3,1)+1>699 ||
(Network2(Posf1(Flight1,1)+1,Posf3(Flight3,1)+1)+2)>(Network2(Posf1(Fli
ght1,1)+1,Posf2(Flight2,1)+1)+Network2(Posf2(Flight2,1)+1,Posf3(Flight3
,1)+1))
%                   if
Network2(Posf1(Flight1,1)+1,Posf4(Flight4,1)+1)==0 ||
Posf4(Flight4,1)+1>699 ||
(Network2(Posf1(Flight1,1)+1,Posf4(Flight4,1)+1)+3)>
(Network2(Posf1(Flight1,1)+1,Posf2(Flight2,1)+1)+Network2(Posf2(Flight2
,1)+1,Posf3(Flight3,1)+1)+Network2(Posf3(Flight3,1)+1,Posf4(Flight4,1)+
1))
%                           if
Network2(Posf2(Flight2,1)+1,Posf4(Flight4,1)+1)==0 ||
Posf4(Flight4,1)+1>699 ||
(Network2(Posf2(Flight2,1)+1,Posf4(Flight4,1)+1)+2)>(Network2(Posf2(Fli
ght2,1)+1,Posf3(Flight3,1)+1)+Network2(Posf3(Flight3,1)+1,Posf4(Flight4
,1)+1))
                              Connect=1;
%                           end
%                   end
%               end
%           end
%       end
  end

  if Start~=Posf2(Flight2,1) %&& Start~=Posf3(Flight3,1) &&
Start~=Posf4(Flight4,1)% && Start~=Posf5(Flight5,1) &&
Start~=Posf6(Flight6,1)

                                                    Cycle=1;


      end


  if Cycle==1 && Distance==1 && Connect==1
  Gain1= Network1(Start+1,Posf1(Flight1,1)+1)+
Network1(Posf1(Flight1,1)+1,Posf2(Flight2,1)+1);
```

```
 % Gain2=
Network1(Posf4(Flight4,1)+1,Posf5(Flight5,1)+1)+Network1(Posf5(Flight5,
1)+1,Posf4(Flight6,1)+1);
  TotalGain=Gain1+Gain2;

  if Start == 321
      MaxLocation1(V,1)=Network1(Posf1(Flight1,1)+1,1);
      MaxLocation1(V,2)=Network1(Posf2(Flight2,1)+1,1);
      MaxLocation1(V,3)=TotalGain;
      V=V+1;

  end

  if Start == 415
      MaxLocation2(V,1)=Network1(Posf1(Flight1,1)+1,1);
      MaxLocation2(V,2)=Network1(Posf2(Flight2,1)+1,1);
      MaxLocation2(V,3)=TotalGain;
      V=V+1;

  end

  if Start == 367
      MaxLocation3(V,1)=Network1(Posf1(Flight1,1)+1,1);
      MaxLocation3(V,2)=Network1(Posf2(Flight2,1)+1,1);
      MaxLocation3(V,3)=TotalGain;
      V=V+1;

  end

  if Start == 207
      MaxLocation4(V,1)=Network1(Posf1(Flight1,1)+1,1);
      MaxLocation4(V,2)=Network1(Posf2(Flight2,1)+1,1);
      MaxLocation4(V,3)=TotalGain;
      V=V+1;

  end

  if Start == 475
      MaxLocation5(V,1)=Network1(Posf1(Flight1,1)+1,1);
      MaxLocation5(V,2)=Network1(Posf2(Flight2,1)+1,1);
      MaxLocation5(V,3)=TotalGain;
      V=V+1;

  end

  if Start == 47
      MaxLocation6(V,1)=Network1(Posf1(Flight1,1)+1,1);
      MaxLocation6(V,2)=Network1(Posf2(Flight2,1)+1,1);
      MaxLocation6(V,3)=TotalGain;
      V=V+1;

  end
```

```
    if Start == 575
        MaxLocation7(V,1)=Network1(Posf1(Flight1,1)+1,1);
        MaxLocation7(V,2)=Network1(Posf2(Flight2,1)+1,1);
        MaxLocation7(V,3)=TotalGain;
        V=V+1;

    end

    if Start == 292
        MaxLocation8(V,1)=Network1(Posf1(Flight1,1)+1,1);
        MaxLocation8(V,2)=Network1(Posf2(Flight2,1)+1,1);
        MaxLocation8(V,3)=TotalGain;
        V=V+1;

    end

    if Start == 290
        MaxLocation9(V,1)=Network1(Posf1(Flight1,1)+1,1);
        MaxLocation9(V,2)=Network1(Posf2(Flight2,1)+1,1);
        MaxLocation9(V,3)=TotalGain;
        V=V+1;

    end

    if Start == 165
        MaxLocation10(V,1)=Network1(Posf1(Flight1,1)+1,1);
        MaxLocation10(V,2)=Network1(Posf2(Flight2,1)+1,1);
        MaxLocation10(V,3)=TotalGain;
        V=V+1;

    end


    if TotalGain>InfectMatrix(Start+1,p+2)
        InfectMatrix(Start+1,2:p+2)=0;
        InfectMatrix(Start+1,Posf1(Flight1,1)+1)=1;
        InfectMatrix(Start+1,Posf2(Flight2,1)+1)=2;

        InfectMatrix(Start+1,p+2)=TotalGain;
    end
    end
    Gain1=0;
    Gain2=0;
    Dis1=0;
    Dis2=0;
%                           end
%                           K6=1;
%                           Posf6=zeros(p+8,1);
%                       end
%                       K5=1;
%                       Posf5=zeros(p+8,1);
```

```
        end
        K2=1;
        Posf2=zeros(p+8,1);
    end
    %disp(Start);
    K1=1;
    Posf1=zeros(p+8,1);

    V=1;

end

MaxMatrix=zeros(p,2);
MaxMatrix(:,1)=InfectMatrix(2:p+1,1);
MaxMatrix(:,2)=InfectMatrix(2:p+1,p+2);

InterestMatrix=zeros(p+1,10);
Best=[158
34
369
87
100
404
401
596
278
443
];



for g=1:1:10
InterestMatrix(:,g)=InfectMatrix(Best(g,1),1:p+1)';
end
```

Matlab code for the cascade network

```
NetworkPercent=NetworkT;

for i=2:1:p+1
    SumRow=sum(NetworkT(i,2:p+1));
    if SumRow>0
    NetworkPercent(i,2:p+1)=NetworkT(i,2:p+1)*(1/SumRow);
    else
         NetworkPercent(i,2:p+1)=0;
    end
end

Network3=zeros(p+9,p+9);
Network3(1:p+1,1:p+1)=NetworkP(:,:);
```

```
Network3(2:p+9,p+2:p+9)=ones(p+8,8);
for d=2:1:p+1
    for f=2:1:p+1
        if NetworkF(d,f)<30
            Network3(d,f)=0;
        end
    end
end
Network4=zeros(p+9,p+9);
Network4(2:p+1,1)=Port(:,1);
Network4(1,2:p+1)=Port(:,1)';
for g=2:1:p+1
    for h=2:1:p+1
        if NetworkDistanceGroup(g,h)>0
            Network4(g,h)=NetworkDistanceGroup(g,h)+1;
        end
    end
end

SpreadMarker = zeros(15,2);

SpreadMarker(1,1)=Network1(496,1);
SpreadMarker(2,1)=Network1(378,1);
SpreadMarker(3,1)=Network1(322,1);
SpreadMarker(4,1)=Network1(161,1);
SpreadMarker(5,1)=Network1(291,1);
SpreadMarker(6,1)=Network1(87,1);
SpreadMarker(7,1)=Network1(407,1);
SpreadMarker(8,1)=Network1(476,1);
SpreadMarker(9,1)=Network1(576,1);
SpreadMarker(10,1)=Network1(48,1);
SpreadMarker(11,1)=Network1(610,1);
SpreadMarker(12,1)=Network1(278,1);
SpreadMarker(13,1)=Network1(293,1);
SpreadMarker(14,1)=Network1(368,1);
SpreadMarker(15,1)=Network1(559,1);

SpreadGage =zeros(p+1,5);
SpreadGage(2:p+1,1)=Network3(2:p+1,1);
TotalInfect=0;


for StartAP=2:1:p+1
    disp(StartAP)
%SAirport=NetworkT(2:p+1,1);
SnewAirport=ones(p+1,2);
SnewAirport(2:p+1,1)=Network3(2:p+1,1);

IAirport2=zeros(p+1,4);
IAirport2(2:p+1,1)=Network3(2:p+1,1);
InewAirport2=IAirport2;

CAirport=zeros(p+1,3);
CAirport(2:p+1,1)=Network3(2:p+1,1);
```

```
CnewAirport=CAirport;

%Sstar=sum(SnewAirport(:,2));
CAirport(StartAP,2)=1;
CnewAirport(StartAP,2)=1;
%Time=1;

for Time=1:1:7
for Q=2:1:p+1
    if CAirport(Q,2)>0
        for P=2:1:p+1
            if (Network3(Q,P)>100 || NetworkPercent(Q,P)>.1) &&
CAirport(P,2)==0 && (Network4(Q,P)<= (Time-CAirport(Q,2)))
                CnewAirport(P,2)=Time;
                CnewAirport(P,3)=Network3(Q,P);
                SnewAirport(P,2)=0;
            else if Network3(Q,P)>0 && IAirport2(P,2)==0 &&
CAirport(P,2)==0 && (Network4(Q,P)<= (Time-CAirport(Q,2)))
                InewAirport2(P,2)=Time;
                InewAirport2(P,3)=Network3(Q,P);
                InewAirport2(P,4)=NetworkPercent(Q,P);
                SnewAirport(P,2)=0;
            else if Network3(Q,P)>0 && IAirport2(P,2)>0 &&
CAirport(P,2)==0 %&& (Network4(Q,P)<= (Time-CAirport(Q,P)))
                InewAirport2(P,2)=Time;
                InewAirport2(P,3)=Network3(Q,P)+InewAirport2(P,3);

InewAirport2(P,4)=NetworkPercent(Q,P)+InewAirport2(P,4);
                %check the above equation
                %IAirport2(P,3)+
                end

                end
            end
            if (InewAirport2(P,3)>100||InewAirport2(P,4)>.1) &&
IAirport2(P,2)>0 && CAirport(P,2)==0
                CnewAirport(P,2)=Time;
                CnewAirport(P,3)=InewAirport2(P,3);
            end
        end
    end
end

IAirport2=InewAirport2;
CAirport=CnewAirport;
%Sstar=sum(SnewAirport(:,2));
end

SpreadMarker(1,2)=CAirport(496,2);
SpreadMarker(2,2)=CAirport(378,2);
SpreadMarker(3,2)=CAirport(322,2);
SpreadMarker(4,2)=CAirport(161,2);
SpreadMarker(5,2)=CAirport(291,2);
SpreadMarker(6,2)=CAirport(87,2);
```

```
SpreadMarker(7,2)=CAirport(407,2);
SpreadMarker(8,2)=CAirport(476,2);
SpreadMarker(9,2)=CAirport(576,2);
SpreadMarker(10,2)=CAirport(48,2);
SpreadMarker(11,2)=CAirport(610,2);
SpreadMarker(12,2)=CAirport(278,2);
SpreadMarker(13,2)=CAirport(293,2);
SpreadMarker(14,2)=CAirport(368,2);
SpreadMarker(15,2)=CAirport(559,2);

SpreadGage(StartAP,2)= sum(SpreadMarker(:,2));
SpreadGage(StartAP,3)= max(SpreadMarker(:,2));
SpreadGage(StartAP,4)= min(SpreadMarker(:,2));

for R1 =1:1:SpreadGage(StartAP,3)
    for R2 =2:1:p+1
        if CAirport(R2,2)== R1
            TotalInfect=TotalInfect+CAirport(R2,3);
        end
    end
end
SpreadGage(StartAP,5)=TotalInfect;
TotalInfect=0;

end
```

Appendix D: Airline Flight Itineraries

Within this appendix are the flight itineraries for various airlines. These itineraries involve up to four flights and highlight key airports used by each airline selected (noted as Airline A, B, C, or D). The results also include itineraries with the most traffic if BioWatch detection units are taken into consideration.

Table 30. Top Ten Itineraries with Airline A

	1	2	3	4	5	Score
1	Los Angeles, CA	Dallas, TX (DFW)	Orlando, FL	Miami, FL	San Juan, PR	191,397
2	San Juan, PR	Miami, FL	Orlando, FL	Dallas, TX (DFW)	Los Angeles, CA	189,943
3	New York City, NY (LaGuardia)	Chicago, IL (O'Hare)	Dallas, TX (DFW)	Los Angeles, CA	Kahului, HI	188,197
4	San Francisco, CA	Los Angeles, CA	Dallas, TX (DFW)	Miami, FL	San Juan, PR	182,652
5	Kahului, HI	Los Angeles, CA	Dallas, TX (DFW)	Chicago, IL (O'Hare)	New York City, NY (LaGuardia)	181,773
6	Lihue, HI	Los Angeles, CA	Dallas, TX (DFW)	Chicago, IL (O'Hare)	New York City, NY (LaGuardia)	178,592
7	Miami, FL	Orlando, FL	Dallas, TX (DFW)	Los Angeles, CA	Honolulu, HI	172,623
8	Honolulu, HI	Los Angeles, CA	Dallas, TX (DFW)	Orlando, FL	Miami, FL	171,885
9	Austin, TX	Dallas, TX (DFW)	Orlando, FL	Miami, FL	San Juan, PR	171,761
10	Boston, MA	Chicago, IL (O'Hare)	Dallas, TX (DFW)	Los Angeles, CA	Kahului, HI	169,272

Table 31. Top Ten Itineraries with Airline A (using BioWatch)

	1	2	3	4	5	Score
1	Austin, TX	Dallas, TX (DFW)	Orlando, FL	Miami, FL	San Juan, PR	171,761
2	San Antonio, TX	Dallas, TX (DFW)	Orlando, FL	Miami, FL	San Juan, PR	168,331
3	San Juan, PR	Miami, FL	Orlando, FL	Dallas, TX (DFW)	San Antonio, TX	163,725
4	Las Vegas, NV	Dallas, TX (DFW)	Orlando, FL	Miami, FL	San Juan, PR	158,391
5	Santa Ana, CA	Dallas, TX (DFW)	Orlando, FL	Miami, FL	San Juan, PR	153,368
6	Phoenix, AZ	Dallas, TX (DFW)	Orlando, FL	Miami, FL	San Juan, PR	150,987
7	Denver, CO	Dallas, TX (DFW)	Orlando, FL	Miami, FL	San Juan, PR	149,751
8	Seattle, WA	Dallas, TX (DFW)	Orlando, FL	Miami, FL	San Juan, PR	147,786
9	Albuquerque, NM	Dallas, TX (DFW)	Orlando, FL	Miami, FL	San Juan, PR	142,003
10	Oklahoma City, OK	Dallas, TX (DFW)	Orlando, FL	Miami, FL	San Juan, PR	141,983

Table 32. Top Ten Itineraries with Airline B

	1	2	3	4	5	Score
1	New York City, NY (LaGuardia)	Charlotte, NC	Dallas, TX (DFW)	Phoenix, AZ	Las Vegas, NV	127,393
2	Boston, MA	Philadelphia, PA	Charlotte, NC	Phoenix, AZ	Santa Ana, CA	125,109
3	Los Angeles, CA	Phoenix, AZ	Dallas, TX (DFW)	Charlotte, NC	New York City, NY (LaGuardia)	124,152
4	Las Vegas, NV	Phoenix, AZ	Dallas, TX (DFW)	Charlotte, NC	New York City, NY (LaGuardia)	122,466
5	San Diego, CA	Phoenix, AZ	Dallas, TX (DFW)	Charlotte, NC	New York City, NY (LaGuardia)	120,859
6	Portland, OR	Phoenix, AZ	Dallas, TX (DFW)	Charlotte, NC	New York City, NY (LaGuardia)	119,262
7	San Francisco, CA	Phoenix, AZ	Dallas, TX (DFW)	Charlotte, NC	New York City, NY (LaGuardia)	118,504
8	Santa Ana, CA	Phoenix, AZ	Charlotte, NC	Philadelphia, PA	Boston, MA	118,018
9	Sacramento, CA	Phoenix, AZ	Charlotte, NC	Philadelphia, PA	Boston, MA	117,852
10	West Palm Beach, FL	Philadelphia, PA	Charlotte, NC	Phoenix, AZ	Las Vegas, NV	116,621

Table 33. Top Ten Itineraries with Airline B (using BioWatch)

	1	2	3	4	5	Score
1	Portland, OR	Phoenix, AZ	Dallas, TX (DFW)	Charlotte, NC	Orlando, FL	114,501
2	Orlando, FL	Charlotte, NC	Dallas, TX (DFW)	Phoenix, AZ	Portland, OR	111,114
3	Santa Ana, CA	Phoenix, AZ	Dallas, TX (DFW)	Charlotte, NC	Orlando, FL	110,815
4	Sacramento, CA	Phoenix, AZ	Dallas, TX (DFW)	Charlotte, NC	Orlando, FL	110,649
5	Baltimore, MD	Charlotte, NC	Dallas, TX (DFW)	Phoenix, AZ	Portland, OR	110,125
6	Newark, NJ	Charlotte, NC	Dallas, TX (DFW)	Phoenix, AZ	Sacramento, CA	107,925
7	San Jose, CA	Phoenix, AZ	Dallas, TX (DFW)	Charlotte, NC	Orlando, FL	107,676
8	Ontario, CA	Phoenix, AZ	Dallas, TX (DFW)	Charlotte, NC	Orlando, FL	106,517
9	Honolulu, HI	Phoenix, AZ	Dallas, TX (DFW)	Charlotte, NC	Orlando, FL	104,807
10	Las Vegas, NV	Phoenix, AZ	Charlotte, NC	Orlando, FL	N/A	104,714

Table 34. Top Ten Itineraries with Airline C

	1	2	3	4	5	Score
1	Newark, NJ	Houston, TX (IAH)	Los Angeles, CA	San Francisco, CA	Kahului, HI	158,759
2	New Orleans, LA	Houston, TX (IAH)	Los Angeles, CA	San Francisco, CA	Honolulu, HI	158,257
3	Kahului, HI	San Francisco, CA	Los Angeles, CA	Houston, TX (IAH)	Newark, NJ	157,841
4	Honolulu, HI	San Francisco, CA	Los Angeles, CA	Houston, TX (IAH)	Orlando, FL	157,209
5	New York City, NY (LaGuardia)	Houston, TX (IAH)	Los Angeles, CA	San Francisco, CA	Honolulu, HI	156,277
6	Orlando, FL	Houston, TX (IAH)	Los Angeles, CA	San Francisco, CA	Honolulu, HI	154,646
7	Kona, HI	San Francisco, CA	Los Angeles, CA	Houston, TX (IAH)	Newark, NJ	153,023
8	Lihue, HI	San Francisco, CA	Los Angeles, CA	Houston, TX (IAH)	Newark, NJ	151,541
9	San Francisco, CA	Los Angeles, CA	Denver, CO	Houston, TX (IAH)	New York City, NY (LaGuardia)	150,738
10	Fort Lauderdale, FL	Houston, TX (IAH)	Los Angeles, CA	San Francisco, CA	Honolulu, HI	147,494

Table 35. Top Ten Itineraries with Airline C (using BioWatch)

	1	2	3	4	5	Score
1	West Palm Beach, FL	Newark, NJ	Denver, CO	Las Vegas, NV	N/A	59,671
2	Las Vegas, NV	Denver, CO	Newark, NJ	West Palm Beach, FL	N/A	59,422
3	Anchorage, AK	Seattle, WA	Newark, NJ	Orlando, FL	N/A	58,481
4	Phoenix, AZ	Denver, CO	Newark, NJ	West Palm Beach, FL	N/A	57,557
5	Portland, OR	Denver, CO	Newark, NJ	West Palm Beach, FL	N/A	55,905
6	Santa Ana, CA	Denver, CO	Newark, NJ	West Palm Beach, FL	N/A	55,524
7	Lincoln, NE	Orlando, FL	Newark, NJ	Seattle, WA	Anchorage, AK	54,075
8	Fort Myer, FL	Orlando, FL	Newark, NJ	Seattle, WA	Anchorage, AK	53,850
9	Orlando, FL	Newark, NJ	Seattle, WA	Anchorage, AK	N/A	53,773
10	Kahului, HI	Sacramento, CA	Denver, CO	Newark, NJ	West Palm Beach, FL	53,618

Table 36. Top Ten Itineraries with Airline D

	1	2	3	4	5	Score
1	Honolulu, HI	Los Angeles, CA	Atlanta, GA	Orlando, FL	New York City, NY (LaGuardia)	181,843
2	New York City, NY (LaGuardia)	Orlando, FL	Atlanta, GA	Los Angeles, CA	Honolulu, HI	180,115
3	Kahului, HI	Los Angeles, CA	Atlanta, GA	Orlando, FL	New York City, NY (LaGuardia)	171,907
4	Seattle, WA	Salt Lake City, UT	Atlanta, GA	Orlando, FL	New York City, NY (LaGuardia)	167,944
5	Kona, HI	Los Angeles, CA	Atlanta, GA	Orlando, FL	New York City, NY (LaGuardia)	167,107
6	Lihue, HI	Los Angeles, CA	Atlanta, GA	Orlando, FL	New York City, NY (LaGuardia)	166,743
7	Los Angeles, CA	Atlanta, GA	Orlando, FL	New York City, NY (LaGuardia)	Portland, ME	165,034
8	Portland, OR	Salt Lake City, UT	Minneapolis, MN	Atlanta, GA	Orlando, FL	163,429
9	San Francisco, CA	Los Angeles, CA	Atlanta, GA	Orlando, FL	New York City, NY (LaGuardia)	163,210
10	Oakland, CA	Los Angeles, CA	Atlanta, GA	Orlando, FL	New York City, NY (LaGuardia)	163,128

Table 37. Top Ten Itineraries with Airline D (using BioWatch)

	1	2	3	4	5	Score
1	Orlando, FL	Detroit, MI	Minneapolis, MN	Seattle, WA	Honolulu, HI	101,079
2	Honolulu, HI	Seattle, WA	Minneapolis, MN	Detroit, MI	Orlando, FL	98,676
3	San Jose, CA	Seattle, WA	Minneapolis, MN	Detroit, MI	Orlando, FL	92,892
4	Seattle, WA	Minneapolis, MN	Detroit, MI	Orlando, FL	Pontiac, MI	92,770
5	Tampa, FL	Detroit, MI	Minneapolis, MN	Seattle, WA	Honolulu, HI	88,358
6	Columbia, SC	Tampa, FL	Detroit, MI	Minneapolis, MN	Seattle, WA	82,812
7	Tallahassee, TN	Tampa, FL	Detroit, MI	Minneapolis, MN	Seattle, WA	82,808
8	Baltimore, MD	Detroit, MI	Minneapolis, MN	Seattle, WA	Honolulu, HI	81,140
9	Miami, FL	Orlando, FL	Detroit, MI	Minneapolis, MN	Portland, OR	80,592
10	Boise, ID	Portland, OR	Minneapolis, MN	Detroit, MI	Orlando, FL	78,385

Appendix E: Two Flight Itineraries (using an International Arrival)

This appendix shows the most trafficked itineraries while using the top ten international airports and two additional flights. Table 22 displays itineraries for all ten international airports with a flight between San Francisco and Los Angeles allowed. Table 23 displays itineraries for all ten international airports without allowing for flights between San Francisco and Los Angeles airports (in order to produce more realistic results). To see the results with BioWatch detection units considered, reference Table 11.

Table 38. Top Ten Itineraries using International Airports and Two Flights

Start at NY

	1	2	Score
1	Los Angeles, CA	San Francisco, CA	260,599
2	Los Angeles, CA	Honolulu, HI	224,046
3	Los Angeles, CA	Las Vegas, NV	218,552
4	Los Angeles, CA	Phoenix, AZ	202,334
5	Los Angeles, CA	Houston, TX	188,724
6	Los Angeles, CA	San Jose, CA	171,356
7	Los Angeles, CA	Oakland, CA	169,542
8	Los Angeles, CA	Sacramento, CA	168,084
9	Los Angeles, CA	Kahului, HI	166,913
10	Orlando, FL	Atlanta, GA	161,884

Start at Atlanta

	1	2	Score
1	Los Angeles, CA	San Francisco, CA	206,057
2	Los Angeles, CA	Honolulu, HI	169,504
3	Orlando, FL	Philadelphia, PA	168,332
4	Orlando, FL	New York City, NY (JFK)	168,108
5	Orlando, FL	Newark, NJ	165,922
6	Los Angeles, CA	Las Vegas, NV	164,010
7	Dallas, TX	Los Angeles, CA	158,816
8	Orlando, FL	Detroit, MI	156,823
9	Orlando, FL	Miami, FL	153,205
10	Orlando, FL	Dallas, TX	152,079

Start at Miami

	1	2	Score
1	Los Angeles, CA	San Francisco, CA	175,914
2	Atlanta, GA	Fort Lauderdale, FL	160,343
3	Atlanta, GA	New York City, NY (LaGuardia)	158,831
4	Orlando, FL	Atlanta, GA	145,027
5	Los Angeles, CA	Honolulu, HI	139,361
6	Dallas, TX	Los Angeles, CA	134,322
7	Los Angeles, CA	Las Vegas, NV	133,867
8	Atlanta, GA	Los Angeles, CA	133,616
9	New York City, NY (LaGuardia)	Fort Lauderdale, FL	129,133
10	Atlanta, GA	Charlotte, NC	128,655

Start at San Francisco

	1	2	Score
1	Los Angeles, CA	New York City, NY (JFK)	270,450
2	Los Angeles, CA	Chicago, IL (O'Hare)	230,063
3	Los Angeles, CA	Dallas, TX	227,053
4	Los Angeles, CA	Las Vegas, NV	226,251
5	Los Angeles, CA	Denver, CO	218,055
6	Los Angeles, CA	Atlanta, GA	215,732
7	Los Angeles, CA	Phoenix, AZ	210,033
8	Los Angeles, CA	Houston, TX (IAH)	196,423
9	Los Angeles, CA	Seattle, WA	194,237
10	Los Angeles, CA	Washington, DC (IAD)	190,144

Start at LA

	1	2	Score
1	San Francisco, CA	Chicago, IL (O'Hare)	207,276
2	San Francisco, CA	Las Vegas, NV	195,557
3	San Francisco, CA	Denver, CO	193,839
4	Chicago, IL (O'Hare)	New York City, NY (LaGuardia)	193,432
5	San Francisco, CA	Seattle, WA	191,871
6	New York City, NY (JFK)	San Juan, PR	190,613
7	Atlanta, GA	Orlando, FL	188,749
8	San Francisco, CA	Dallas, TX	187,241
9	San Francisco, CA	San Diego, CA	186,997
10	Atlanta, GA	Fort Lauderdale, FL	180,218

Start at Houston (IAH)

	1	2	Score
1	Los Angeles, CA	New York City, NY (JFK)	187,502
2	Los Angeles, CA	San Francisco, CA	185,350
3	Chicago, IL (O'Hare)	New York City, NY (LaGuardia)	154,124
4	Los Angeles, CA	Honolulu, HI	148,797
5	Atlanta, GA	Orlando, FL	147,898
6	Los Angeles, CA	Las Vegas, NV	143,303
7	Atlanta, GA	New York City, NY (LaGuardia)	137,855
8	Orlando, FL	Atlanta, GA	132,491
9	Dallas, TX	Los Angeles, CA	132,438
10	Denver, CO	Phoenix, AZ	131,211

Start at Newark

	1	2	Score
1	Los Angeles, CA	New York City, NY (JFK)	164,884
2	Los Angeles, CA	San Francisco, CA	162,732
3	Orlando, FL	Atlanta, GA	158,667
4	Atlanta, GA	Orlando, FL	150,132
5	Atlanta, GA	Fort Lauderdale, FL	141,601
6	Chicago, IL (O'Hare)	Los Angeles, CA	133,001
7	Los Angeles, CA	Honolulu, HI	126,179
8	Los Angeles, CA	Las Vegas, NV	120,685
9	San Francisco, CA	New York City, NY (JFK)	119,465
10	Chicago, IL (O'Hare)	San Francisco, CA	119,407

Start at Washington (IAD)

	1	2	Score
1	San Francisco, CA	Los Angeles, CA	190,166
2	Los Angeles, CA	San Francisco, CA	181,190
3	Los Angeles, CA	Honolulu, HI	144,637
4	New York City, NY (JFK)	Los Angeles, CA	144,597
5	Los Angeles, CA	Las Vegas, NV	139,143
6	Atlanta, GA	Orlando, FL	137,472
7	Orlando, FL	Atlanta, GA	120,430
8	Denver, CO	Phoenix, AZ	118,969
9	Denver, CO	Los Angeles, CA	118,710
10	San Francisco, CA	Las Vegas, NV	117,425

Start at Chicago (Ohare)

	1	2	Score
1	Los Angeles, CA	San Francisco, CA	218,512
2	San Francisco, CA	Los Angeles, CA	216,398
3	Los Angeles, CA	Honolulu, HI	181,959
4	Los Angeles, CA	Las Vegas, NV	176,465
5	Atlanta, GA	Orlando, FL	163,910
6	Dallas, TX	Los Angeles, CA	163,397
7	Atlanta, GA	Fort Lauderdale, FL	155,379
8	San Francisco, CA	Las Vegas, NV	143,657
9	New York City, NY (LaGuardia)	Orlando, FL	142,572
10	New York City, NY (LaGuardia)	Washington, DC (DCA)	136,206

Start at Dallas

	1	2	Score
1	Los Angeles, CA	San Francisco, CA	218,230
2	San Francisco, CA	Los Angeles, CA	197,676
3	Atlanta, GA	Orlando, FL	181,926
4	Los Angeles, CA	Honolulu, HI	181,677
5	Los Angeles, CA	Las Vegas, NV	176,183
6	Atlanta, GA	Fort Lauderdale, FL	173,395
7	Chicago, IL (O'Hare)	New York City, NY (LaGuardia)	171,992
8	Atlanta, GA	New York City, NY (LaGuardia)	171,883
9	Denver, CO	Los Angeles, CA	150,596
10	Atlanta, GA	Tampa, FL	149,049

Table 39. Top Ten using International Airports and Two Flights (No SFA LAX Connection)

Start at NY

	1	2	Score
1	Los Angeles, CA	Honolulu, HI	224,046
2	Los Angeles, CA	Las Vegas, NV	218,552
3	Los Angeles, CA	Phoenix, AZ	202,334
4	Los Angeles, CA	Houston, TX	188,724
5	Los Angeles, CA	San Jose, CA	171,356
6	Los Angeles, CA	Oakland, CA	169,542
7	Los Angeles, CA	Sacramento, CA	168,084
8	Los Angeles, CA	Kahului, HI	166,913
9	Orlando, FL	Atlanta, GA	161,884
10	Los Angeles, CA	San Diego, CA	158,349

Start at Atlanta

	1	2	Score
1	Los Angeles, CA	Honolulu, HI	169,504
2	Orlando, FL	Philadelphia, PA	168,332
3	Orlando, FL	New York City, NY (JFK)	168,108
4	Orlando, FL	Newark, NJ	165,922
5	Los Angeles, CA	Las Vegas, NV	164,010
6	Dallas, TX	Los Angeles, CA	158,816
7	Orlando, FL	Detroit, MI	156,823
8	Orlando, FL	Miami, FL	153,205
9	Orlando, FL	Dallas, TX	152,079
10	Orlando, FL	San Juan, PR	150,467

Start at Miami

	1	2	Score
1	Atlanta, GA	Fort Lauderdale, FL	160,343
2	Atlanta, GA	New York City, NY (LaGuardia)	158,831
3	Orlando, FL	Atlanta, GA	145,027
4	Los Angeles, CA	Honolulu, HI	139,361
5	Dallas, TX	Los Angeles, CA	134,322
6	Los Angeles, CA	Las Vegas, NV	133,867
7	Atlanta, GA	Los Angeles, CA	133,616
8	New York City, NY (LaGuardia)	Fort Lauderdale, FL	129,133
9	Atlanta, GA	Charlotte, NC	128,655
10	Atlanta, GA	Dallas, TX	124,963

Start at San Francisco

	1	2	Score
1	Chicago, IL (O'Hare)	New York City, NY (LaGuardia)	182,125
2	Atlanta, GA	Orlando, FL	156,522
3	Las Vegas, NV	Los Angeles, CA	150,650
4	Atlanta, GA	Fort Lauderdale, FL	147,991
5	New York City, NY (JFK)	San Juan, PR	146,519
6	Atlanta, GA	New York City, NY (LaGuardia)	146,479
7	Chicago, IL (O'Hare)	Minneapolis, MN	143,631
8	Las Vegas, NV	Denver, CO	142,463
9	Chicago, IL (O'Hare)	Boston, MA	135,654
10	Denver, CO	Dallas, TX	132,319

Start at LA

	1	2	Score
1	Chicago, IL (O'Hare)	New York City, NY (LaGuardia)	193,432
2	New York City, NY (JFK)	San Juan, PR	190,613
3	Atlanta, GA	Orlando, FL	188,749
4	Atlanta, GA	Fort Lauderdale, FL	180,218
5	Atlanta, GA	New York City, NY (LaGuardia)	178,706
6	New York City, NY (JFK)	Boston, MA	172,605
7	Las Vegas, NV	Denver, CO	161,677
8	New York City, NY (JFK)	Buffalo, NY	156,580
9	Dallas, TX	Atlanta, GA	156,184
10	Dallas, TX	Chicago, IL (O'Hare)	155,898

Start at Houston (IAH)

	1	2	Score
1	Los Angeles, CA	New York City, NY (JFK)	187,502
2	Chicago, IL (O'Hare)	New York City, NY (LaGuardia)	154,124
3	Los Angeles, CA	Honolulu, HI	148,797
4	Atlanta, GA	Orlando, FL	147,898
5	Los Angeles, CA	Las Vegas, NV	143,303
6	Atlanta, GA	New York City, NY (LaGuardia)	137,855
7	Orlando, FL	Atlanta, GA	132,491
8	Dallas, TX	Los Angeles, CA	132,438
9	Denver, CO	Phoenix, AZ	131,211
10	Denver, CO	Los Angeles, CA	130,952

Start at Newark

	1	2	Score
1	Los Angeles, CA	New York City, NY (JFK)	164,884
2	Orlando, FL	Atlanta, GA	158,667
3	Atlanta, GA	Orlando, FL	150,132
4	Atlanta, GA	Fort Lauderdale, FL	141,601
5	Chicago, IL (O'Hare)	Los Angeles, CA	133,001
6	Los Angeles, CA	Honolulu, HI	126,179
7	Los Angeles, CA	Las Vegas, NV	120,685
8	San Francisco, CA	New York City, NY (JFK)	119,465
9	Chicago, IL (O'Hare)	San Francisco, CA	119,407
10	Dallas, TX	Los Angeles, CA	118,326

Start at Washington (IAD)

	1	2	Score
1	Los Angeles, CA	Honolulu, HI	144,637
2	New York City, NY (JFK)	Los Angeles, CA	144,597
3	Los Angeles, CA	Las Vegas, NV	139,143
4	Atlanta, GA	Orlando, FL	137,472
5	Orlando, FL	Atlanta, GA	120,430
6	Denver, CO	Phoenix, AZ	118,969
7	Denver, CO	Los Angeles, CA	118,710
8	San Francisco, CA	Las Vegas, NV	117,425
9	Denver, CO	Las Vegas, NV	116,307
10	New York City, NY (LaGuardia\)	Atlanta, GA	114,296

Start at Chicago (Ohare)

	1	2	Score
1	Los Angeles, CA	Honolulu, HI	181,959
2	Los Angeles, CA	Las Vegas, NV	176,465
3	Atlanta, GA	Orlando, FL	163,910
4	Dallas, TX	Los Angeles, CA	163,397
5	Atlanta, GA	Fort Lauderdale, FL	155,379
6	San Francisco, CA	Las Vegas, NV	143,657
7	New York City, NY (LaGuardia)	Orlando, FL	142,572
8	New York City, NY (LaGuardia)	Washington, DC (DCA)	136,206
9	Denver, CO	Phoenix, AZ	135,787
10	Denver, CO	Los Angeles, CA	135,528

Start at Dallas

	1	2	Score
1	Atlanta, GA	Orlando, FL	181,926
2	Los Angeles, CA	Honolulu, HI	181,677
3	Los Angeles, CA	Las Vegas, NV	176,183
4	Atlanta, GA	Fort Lauderdale, FL	173,395
5	Chicago, IL (O'Hare)	New York City, NY (LaGuardia)	171,992
6	Atlanta, GA	New York City, NY (LaGuardia)	171,883
7	Denver, CO	Los Angeles, CA	150,596
8	Atlanta, GA	Tampa, FL	149,049
9	Denver, CO	Las Vegas, NV	148,193
10	Orlando, FL	Atlanta, GA	146,698

Appendix F: Overall Results

By counting the number of times airports showed up in the analysis of four flight itineraries, Table 24 highlights critical airports that should be equipped with BioWatch if they are not equipped already. Table 25 highlights similar airports based on the results of the international airports with two flight itineraries.

Table 40. Airport Results from Four Flight Itineraries

	Appearance										
Airport	W	W Bio	A	A Bio	B	B Bio	C	C Bio	D	D Bio	Total
Orlando, FL	3	7	5	10	0	8	2	4	10	6	55
Dallas, TX	4	10	10	10	6	9	0	0	0	0	49
Honolulu, HI	8	3	2	0	0	1	5	0	2	4	25
Phoenix, AZ	0	3	0	1	10	10	0	1	0	0	25
Charlotte, NC	0	1	0	0	10	10	0	0	0	0	21
San Juan, PR	2	3	4	10	0	0	0	0	0	0	19
Seattle, WA	0	3	0	1	0	0	0	4	1	8	17
Miami, FL	0	0	6	10	0	0	0	0	0	1	17
Denver, CO	0	7	0	1	0	0	1	6	0	0	15
Newark, NJ	0	0	0	0	0	1	4	10	0	0	15
Las Vegas	2	4	0	1	3	1	0	2	0	0	13
Minneapolis, MN	0	0	0	0	0	0	0	0	1	10	11
Kahului, HI	0	3	3	0	0	0	2	1	1	0	10
Detroit, MI	0	0	0	0	0	0	0	0	0	10	10
Portland, OR	0	0	0	0	1	3	0	1	1	2	8
West Palm Beach, FL	0	0	0	0	1	0	0	6	0	0	7
Achorage, AK	0	2	0	0	0	0	0	4	0	0	6
Kona, HI	3	0	0	0	0	0	1	0	1	0	5
Santa Ana, CA	0	0	0	1	2	1	0	1	0	0	5
Lihue, HI	1	0	1	0	0	0	1	0	1	0	4
Tampa, FL	1	0	0	0	0	0	0	0	0	3	4
Sacramento, CA	0	0	0	0	1	2	0	1	0	0	4
Austin, TX	0	1	1	1	0	0	0	0	0	0	3
San Antonio, TX	0	1	0	2	0	0	0	0	0	0	3
Fort Lauderdale, FL	1	0	0	0	0	0	1	0	0	0	2

Oakland, CA	0	1	0	0	0	0	0	0	1	0	2
Baltimore, MD	0	0	0	0	0	1	0	0	0	1	2
San Jose, CA	0	0	0	0	0	1	0	0	0	1	2
Salt Lake City, UT	0	0	0	0	0	0	0	0	2	0	2
Burbank, CA	0	1	0	0	0	0	0	0	0	0	1
Albuquerque, NM	0	0	0	1	0	0	0	0	0	0	1
Oklahoma City, OK	0	0	0	1	0	0	0	0	0	0	1
Ontario, CA	0	0	0	0	0	1	0	0	0	0	1
New Orleans	0	0	0	0	0	0	1	0	0	0	1
Lincoln, NE	0	0	0	0	0	0	0	1	0	0	1
Fort Myer, FL	0	0	0	0	0	0	0	1	0	0	1
Portland, ME	0	0	0	0	0	0	0	0	1	0	1
Pontiac, MI	0	0	0	0	0	0	0	0	0	1	1
Columbia, SC	0	0	0	0	0	0	0	0	0	1	1
Tallahassee, TN	0	0	0	0	0	0	0	0	0	1	1
Boise, ID	0	0	0	0	0	0	0	0	0	1	1

Table 41. Airport Results from Two Flight Scenario

	Appearance	
Airport	2 Flt	2 Flt Bio
Denver, CO	12	12
Dallas, TX	10	10
Orlando, FL	21	7
Las Vegas	15	6
Phoenix, AZ	4	5
Seattle, WA	0	3
Honolulu, HI	8	2
Kahului, HI	1	2
Charlotte, NC	1	2
San Juan, PR	3	1
Miami, FL	1	1
Sacramento, CA	1	1
Newark, NJ	1	1
Detroit, MI	1	1
Austin, TX	0	1
San Antonio, TX	0	1
Santa Ana, CA	0	1
Portland, OR	0	1
Salt Lake City, UT	0	1
Omaha, NE	0	1
Fort Lauderdale, FL	7	0
Tampa, FL	1	0
Oakland, CA	1	0
San Jose, CA	1	0
Minneapolis, MN	1	0
Buffalo, NY	1	0

Table 42. List of Airports in GSA Program (in alphabetical order)

City	Airport Code	Number of GSA
ABERDEEN, SD	ABR	2
ABILENE, TX	ABI	15
AGUADILLA, PR	BQN	2
AKRON, OH	CAK	7
ALBANY, GA	ABY	5
ALBANY, NY	ALB	33
ALBUQUERQUE, NM	ABQ	107
ALEXANDRIA, LA	AEX	47
ALLENTOWN, PA	ABE	3
AMARILLO, TX	AMA	12
ANCHORAGE, AK	ANC	81
APPLETON, WI	ATW	1
ARCATA/EUREKA, CA	ACV	5
ASHEVILLE, NC	AVL	5
ASPEN, CO	ASE	1
ATLANTA, GA	ATL	235
AUGUSTA, GA	AGS	49
AUSTIN, TX	AUS	80
BAKERSFIELD, CA	BFL	3
BANGOR, ME	BGR	7
BARROW, AK	BRW	2
BATON ROUGE, LA	BTR	15
BECKLEY, WV	BKW	1
BELLINGHAM, WA	BLI	6
BILLINGS, MT	BIL	12
BINGHAMTON, NY	BGM	2
BIRMINGHAM, AL	BHM	54
BISMARCK, ND	BIS	9
BLOOMINGTON, IL	BMI	1
BOISE, ID	BOI	41
BOSTON, MA	BOS	128
BOZEMAN, MT	BZN	7
BROWNSVILLE, TX	BRO	6
BRUNSWICK, GA	BQK	4
BUFFALO, NY	BUF	34
BURLINGTON, VT	BTV	22
BUTTE, MT	BTM	1

CARLSBAD, CA	CLD	2
CASPER, WY	CPR	3
CEDAR CITY, UT	CDC	1
CEDAR RAPIDS, IA	CID	20
CHAMPAIGN, IL	CMI	2
CHARLESTON, SC	CHS	74
CHARLESTON, WV	CRW	21
CHARLOTTE, NC	CLT	59
CHARLOTTESVILLE, VA	CHO	11
CHATTANOOGA, TN	CHA	14
CHICAGO, IL	CHI	40
CHICAGO, IL	MDW	22
CHICAGO, IL	ORD	44
CINCINNATI, OH	CVG	52
CLEVELAND, OH	CLE	59
CODY, WY	COD	2
COLLEGE STATION, TX	CLL	1
COLORADO SPRINGS, CO	COS	83
COLUMBIA, MO	COU	1
COLUMBIA, SC	CAE	88
COLUMBUS, GA	CSG	29
COLUMBUS, OH	CMH	59
CORDOVA, AK	CDV	1
CORPUS CHRISTI, TX	CRP	25
DALLAS-FT. WORTH, TX	DAL	20
DALLAS-FT. WORTH, TX	DFW	150
DAYTON, OH	DAY	72
DAYTONA BEACH, FL	DAB	1
DENVER, CO	DEN	142
DES MOINES, IA	DSM	27
DETROIT, MI	DTW	93
DOTHAN, AL	DHN	24
DUBUQUE, IA	DBQ	1
DULUTH, MN	DLH	4
DURANGO, CO	DRO	1
DUTCH HARBOR, AK	DUT	1
EAU CLAIRE, WI	EAU	1
EL PASO, TX	ELP	79
ELKO, NV	EKO	2

ERIE, PA	ERI	1
EUGENE, OR	EUG	8
EVANSVILLE, IN	EVV	6
FAIRBANKS, AK	FAI	11
FARGO, ND	FAR	10
FAYETTEVILLE, NC	FAY	58
FLINT, MI	FNT	2
FRESNO, CA	FAT	21
FT. LAUDERDALE, FL	FLL	42
FT. SMITH, AR	FSM	3
FT. WALTON BEACH, FL	VPS	8
FT. WAYNE, IN	FWA	5
GAINESVILLE, FL	GNV	2
GILLETTE, WY	GCC	1
GRAND FORKS, ND	GFK	7
GRAND JUNCTION, CO	GJT	2
GRAND RAPIDS, MI	GRR	15
GREAT FALLS, MT	GTF	8
GREEN BAY, WI	GRB	10
GREENSBORO, NC	GSO	16
GREENVILLE, SC	GSP	11
GUAM,	GUM	10
GULFPORT, MS	GPT	52
HANCOCK, MI	CMX	2
HARLINGEN, TX	HRL	7
HARRISBURG, PA	MDT	33
HARTFORD, CT	BDL	64
HELENA, MT	HLN	6
HILO, HI	ITO	4
HOBBS, NM	HOB	1
HONOLULU, HI	HNL	101
HOUSTON, TX	HOU	54
HOUSTON, TX	IAH	58
HUNTSVILLE, AL	HSV	69
IDAHO FALLS, ID	IDA	2
INDIANAPOLIS, IN	IND	60
ISLIP, NY	ISP	1
JACKSON, MS	JAN	40
JACKSONVILLE, FL	JAX	71
JACKSONVILLE, NC	OAJ	28

JUNEAU, AK	JNU	7
KAHULUI, HI	OGG	3
KALAMAZOO, MI	AZO	15
KALISPELL, MT	FCA	3
KANSAS CITY, MO	MCI	60
KAUAI, HI	LIH	2
KETCHIKAN, AK	KTN	5
KEY WEST, FL	EYW	19
KILLEEN GRAY AAF, TX	GRK	51
KING SALMON, AK	AKN	1
KLAMATH FALLS, OR	LMT	1
KNOXVILLE, TN	TYS	2
KODIAK, AK	ADQ	4
KONA, HI	KOA	4
LA CROSSE, WI	LSE	29
LAFAYETTE, LA	LFT	2
LAKE CHARLES, LA	LCH	1
LANSING, MI	LAN	7
LAREDO, TX	LRD	4
LAS VEGAS, NV	LAS	69
LAWTON, OK	LAW	18
LEWISTON, ID	LWS	2
LEXINGTON, KY	LEX	18
LINCOLN, NE	LNK	2
LITTLE ROCK, AR	LIT	43
LOS ANGELES, CA	BUR	12
LOS ANGELES, CA	LAX	118
LOS ANGELES, CA	LGB	8
LOS ANGELES, CA	ONT	18
LOUISVILLE, KY	SDF	24
LUBBOCK, TX	LBB	9
MADISON, WI	MSN	20
MANCHESTER, NH	MHT	12
MANHATTAN, KS	MHK	6
MCALLEN, TX	MFE	5
MEDFORD, OR	MFR	3
MELBOURNE, FL	MLB	1
MEMPHIS, TN	MEM	39
MIAMI, FL	MIA	76
MILWAUKEE, WI	MKE	22

MINNEAPOLIS-ST.PAUL, MN	MSP	46
MINOT, ND	MOT	8
MISSOULA, MT	MSO	7
MOBILE, AL	MOB	16
MODESTO, CA	MOD	1
MOLINE, IL	MLI	21
MONTEREY, CA	MRY	13
MONTGOMERY, AL	MGM	29
NASHVILLE, TN	BNA	100
NEW BERN, NC	EWN	17
NEW ORLEANS, LA	MSY	47
NEW YORK, NY	JFK	32
NEW YORK, NY	LGA	48
NEW YORK, NY	NYC	98
NEWARK, NJ	EWR	76
NEWPORT NEWS, VA	PHF	20
NOME, AK	OME	1
NORFOLK, VA	ORF	80
NORTH BEND, OR	OTH	1
OKLAHOMA CITY, OK	OKC	43
OMAHA, NE	OMA	31
ORANGE COUNTY, CA	SNA	4
ORLANDO, FL	MCO	66
PALM SPRINGS, CA	PSP	10
PANAMA CITY, FL	ECP	36
PASCO, WA	PSC	3
PENSACOLA, FL	PNS	27
PEORIA, IL	PIA	3
PHILADELPHIA, PA	PHL	54
PHOENIX/SCOTTSDALE, AZ	PHX	36
PITTSBURGH, PA	PIT	26
PORTLAND, ME	PWM	4
PORTLAND, OR	PDX	38
PROVIDENCE, RI	PVD	16
PULLMAN, WA	PUW	1
RALEIGH-DURHAM, NC	RDU	42
RAPID CITY, SD	RAP	9
REDMOND, OR	RDM	1
RENO, NV	RNO	12

RICHMOND, VA	RIC	27
ROANOKE, VA	ROA	3
ROCHESTER, NY	ROC	5
SACRAMENTO, CA	SMF	12
SAGINAW, MI	MBS	1
SALT LAKE CITY, UT	SLC	24
SAN ANGELO, TX	SJT	3
SAN ANTONIO, TX	SAT	51
SAN DIEGO, CA	SAN	62
SAN FRANCISCO, CA	OAK	13
SAN FRANCISCO, CA	SFO	49
SAN JOSE, CA	SJC	5
SAN JUAN, PR	SJU	15
SAN LUIS OBISPO, CA	SBP	4
SANTA BARBARA, CA	SBA	3
SAVANNAH, GA	SAV	15
SCRANTON, PA	AVP	22
SEATTLE-TACOMA, WA	SEA	60
SHREVEPORT, LA	SHV	6
SIOUX FALLS, SD	FSD	11
SPOKANE, WA	GEG	34
SPRINGFIELD, MO	SGF	2
ST. GEORGE, UT	SGU	1
ST. LOUIS, MO	STL	28
STATE COLLEGE, PA	SCE	1
SYRACUSE, NY	SYR	5
TAMPA, FL	TPA	25
TUCSON, AZ	TUS	12
TULSA, OK	TUL	2
WACO, TX	ACT	5
WALLA WALLA, WA	ALW	1
WASHINGTON, DC	BWI	124
WASHINGTON, DC	DCA	144
WASHINGTON, DC	IAD	88
WASHINGTON, DC	WAS	163
WATERTOWN, NY	ART	1
WAUSAU, WI	CWA	2
WENATCHEE, WA	EAT	2
WEST PALM BEACH, FL	PBI	9
WICHITA FALLS, TX	SPS	3

WICHITA, KS	ICT	28
WILMINGTON, NC	ILM	9
YUMA, AZ	YUM	1

Table 43. List of Airports in GSA Program (in order of number of GSA city pairs)

City	Airport Code	Number of GSA
ATLANTA, GA	ATL	235
WASHINGTON, DC	WAS	163
DALLAS-FT. WORTH, TX	DFW	150
WASHINGTON, DC	DCA	144
DENVER, CO	DEN	142
BOSTON, MA	BOS	128
WASHINGTON, DC	BWI	124
LOS ANGELES, CA	LAX	118
ALBUQUERQUE, NM	ABQ	107
HONOLULU, HI	HNL	101
NASHVILLE, TN	BNA	100
NEW YORK, NY	NYC	98
DETROIT, MI	DTW	93
COLUMBIA, SC	CAE	88
WASHINGTON, DC	IAD	88
COLORADO SPRINGS, CO	COS	83
ANCHORAGE, AK	ANC	81
AUSTIN, TX	AUS	80
NORFOLK, VA	ORF	80
EL PASO, TX	ELP	79
MIAMI, FL	MIA	76
NEWARK, NJ	EWR	76
CHARLESTON, SC	CHS	74
DAYTON, OH	DAY	72
JACKSONVILLE, FL	JAX	71
HUNTSVILLE, AL	HSV	69
LAS VEGAS, NV	LAS	69
ORLANDO, FL	MCO	66
HARTFORD, CT	BDL	64

SAN DIEGO, CA	SAN	62
INDIANAPOLIS, IN	IND	60
KANSAS CITY, MO	MCI	60
SEATTLE-TACOMA, WA	SEA	60
CHARLOTTE, NC	CLT	59
CLEVELAND, OH	CLE	59
COLUMBUS, OH	CMH	59
FAYETTEVILLE, NC	FAY	58
HOUSTON, TX	IAH	58
BIRMINGHAM, AL	BHM	54
HOUSTON, TX	HOU	54
PHILADELPHIA, PA	PHL	54
CINCINNATI, OH	CVG	52
GULFPORT, MS	GPT	52
KILLEEN GRAY AAF, TX	GRK	51
SAN ANTONIO, TX	SAT	51
AUGUSTA, GA	AGS	49
SAN FRANCISCO, CA	SFO	49
NEW YORK, NY	LGA	48
ALEXANDRIA, LA	AEX	47
NEW ORLEANS, LA	MSY	47
MINNEAPOLIS-ST.PAUL, MN	MSP	46
CHICAGO, IL	ORD	44
LITTLE ROCK, AR	LIT	43
OKLAHOMA CITY, OK	OKC	43
FT. LAUDERDALE, FL	FLL	42
RALEIGH-DURHAM, NC	RDU	42
BOISE, ID	BOI	41
CHICAGO, IL	CHI	40
JACKSON, MS	JAN	40
MEMPHIS, TN	MEM	39
PORTLAND, OR	PDX	38
PANAMA CITY, FL	ECP	36
PHOENIX/SCOTTSDALE, AZ	PHX	36
BUFFALO, NY	BUF	34
SPOKANE, WA	GEG	34
ALBANY, NY	ALB	33
HARRISBURG, PA	MDT	33
NEW YORK, NY	JFK	32

OMAHA, NE	OMA	31
COLUMBUS, GA	CSG	29
LA CROSSE, WI	LSE	29
MONTGOMERY, AL	MGM	29
JACKSONVILLE, NC	OAJ	28
ST. LOUIS, MO	STL	28
WICHITA, KS	ICT	28
DES MOINES, IA	DSM	27
PENSACOLA, FL	PNS	27
RICHMOND, VA	RIC	27
PITTSBURGH, PA	PIT	26
CORPUS CHRISTI, TX	CRP	25
TAMPA, FL	TPA	25
DOTHAN, AL	DHN	24
LOUISVILLE, KY	SDF	24
SALT LAKE CITY, UT	SLC	24
BURLINGTON, VT	BTV	22
CHICAGO, IL	MDW	22
MILWAUKEE, WI	MKE	22
SCRANTON, PA	AVP	22
CHARLESTON, WV	CRW	21
FRESNO, CA	FAT	21
MOLINE, IL	MLI	21
CEDAR RAPIDS, IA	CID	20
DALLAS-FT. WORTH, TX	DAL	20
MADISON, WI	MSN	20
NEWPORT NEWS, VA	PHF	20
KEY WEST, FL	EYW	19
LAWTON, OK	LAW	18
LEXINGTON, KY	LEX	18
LOS ANGELES, CA	ONT	18
NEW BERN, NC	EWN	17
GREENSBORO, NC	GSO	16
MOBILE, AL	MOB	16
PROVIDENCE, RI	PVD	16
ABILENE, TX	ABI	15
BATON ROUGE, LA	BTR	15
GRAND RAPIDS, MI	GRR	15
KALAMAZOO, MI	AZO	15
SAN JUAN, PR	SJU	15

SAVANNAH, GA	SAV	15
CHATTANOOGA, TN	CHA	14
MONTEREY, CA	MRY	13
SAN FRANCISCO, CA	OAK	13
AMARILLO, TX	AMA	12
BILLINGS, MT	BIL	12
LOS ANGELES, CA	BUR	12
MANCHESTER, NH	MHT	12
RENO, NV	RNO	12
SACRAMENTO, CA	SMF	12
TUCSON, AZ	TUS	12
CHARLOTTESVILLE, VA	CHO	11
FAIRBANKS, AK	FAI	11
GREENVILLE, SC	GSP	11
SIOUX FALLS, SD	FSD	11
FARGO, ND	FAR	10
GREEN BAY, WI	GRB	10
GUAM,	GUM	10
PALM SPRINGS, CA	PSP	10
BISMARCK, ND	BIS	9
LUBBOCK, TX	LBB	9
RAPID CITY, SD	RAP	9
WEST PALM BEACH, FL	PBI	9
WILMINGTON, NC	ILM	9
EUGENE, OR	EUG	8
FT. WALTON BEACH, FL	VPS	8
GREAT FALLS, MT	GTF	8
LOS ANGELES, CA	LGB	8
MINOT, ND	MOT	8
AKRON, OH	CAK	7
BANGOR, ME	BGR	7
BOZEMAN, MT	BZN	7
GRAND FORKS, ND	GFK	7
HARLINGEN, TX	HRL	7
JUNEAU, AK	JNU	7
LANSING, MI	LAN	7
MISSOULA, MT	MSO	7
BELLINGHAM, WA	BLI	6
BROWNSVILLE, TX	BRO	6
EVANSVILLE, IN	EVV	6

HELENA, MT	HLN	6
MANHATTAN, KS	MHK	6
SHREVEPORT, LA	SHV	6
ALBANY, GA	ABY	5
ARCATA/EUREKA, CA	ACV	5
ASHEVILLE, NC	AVL	5
FT. WAYNE, IN	FWA	5
KETCHIKAN, AK	KTN	5
MCALLEN, TX	MFE	5
ROCHESTER, NY	ROC	5
SAN JOSE, CA	SJC	5
SYRACUSE, NY	SYR	5
WACO, TX	ACT	5
BRUNSWICK, GA	BQK	4
DULUTH, MN	DLH	4
HILO, HI	ITO	4
KODIAK, AK	ADQ	4
KONA, HI	KOA	4
LAREDO, TX	LRD	4
ORANGE COUNTY, CA	SNA	4
PORTLAND, ME	PWM	4
SAN LUIS OBISPO, CA	SBP	4
ALLENTOWN, PA	ABE	3
BAKERSFIELD, CA	BFL	3
CASPER, WY	CPR	3
FT. SMITH, AR	FSM	3
KAHULUI, HI	OGG	3
KALISPELL, MT	FCA	3
MEDFORD, OR	MFR	3
PASCO, WA	PSC	3
PEORIA, IL	PIA	3
ROANOKE, VA	ROA	3
SAN ANGELO, TX	SJT	3
SANTA BARBARA, CA	SBA	3
WICHITA FALLS, TX	SPS	3
ABERDEEN, SD	ABR	2
AGUADILLA, PR	BQN	2
BARROW, AK	BRW	2
BINGHAMTON, NY	BGM	2
CARLSBAD, CA	CLD	2

CHAMPAIGN, IL	CMI	2
CODY, WY	COD	2
ELKO, NV	EKO	2
FLINT, MI	FNT	2
GAINESVILLE, FL	GNV	2
GRAND JUNCTION, CO	GJT	2
HANCOCK, MI	CMX	2
IDAHO FALLS, ID	IDA	2
KAUAI, HI	LIH	2
KNOXVILLE, TN	TYS	2
LAFAYETTE, LA	LFT	2
LEWISTON, ID	LWS	2
LINCOLN, NE	LNK	2
SPRINGFIELD, MO	SGF	2
TULSA, OK	TUL	2
WAUSAU, WI	CWA	2
WENATCHEE, WA	EAT	2
APPLETON, WI	ATW	1
ASPEN, CO	ASE	1
BECKLEY, WV	BKW	1
BLOOMINGTON, IL	BMI	1
BUTTE, MT	BTM	1
CEDAR CITY, UT	CDC	1
COLLEGE STATION, TX	CLL	1
COLUMBIA, MO	COU	1
CORDOVA, AK	CDV	1
DAYTONA BEACH, FL	DAB	1
DUBUQUE, IA	DBQ	1
DURANGO, CO	DRO	1
DUTCH HARBOR, AK	DUT	1
EAU CLAIRE, WI	EAU	1
ERIE, PA	ERI	1
GILLETTE, WY	GCC	1
HOBBS, NM	HOB	1
ISLIP, NY	ISP	1
KING SALMON, AK	AKN	1
KLAMATH FALLS, OR	LMT	1
LAKE CHARLES, LA	LCH	1
MELBOURNE, FL	MLB	1
MODESTO, CA	MOD	1

NOME, AK	OME	1
NORTH BEND, OR	OTH	1
PULLMAN, WA	PUW	1
REDMOND, OR	RDM	1
SAGINAW, MI	MBS	1
ST. GEORGE, UT	SGU	1
STATE COLLEGE, PA	SCE	1
WALLA WALLA, WA	ALW	1
WATERTOWN, NY	ART	1
YUMA, AZ	YUM	1

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14. ABSTRACT

Biological weapons are one of the top five threats identified by the Department of Defense in the United States. While most people commonly associate weapons of mass destruction only with atomic bombs, biological agents still have the ability to inflict mass casualties and panic. By strategically placing bioweapon detection units, known as BioWatch, in various airports, a disease spread could be detected and mitigated before country wide dispersal of the disease occurs. Key cities to invest this program are investigated through network analysis of flight itineraries with large volumes of traffic. In addition to analyzing an airport network, there is also the possibility that an attack could still succeed and infect a city. Should this occur, the current Center for Disease Control policy is to trace sources of infections and vaccinate people suspected of harboring the disease. Kaplan *et al.*, as well as others, have argued for mass vaccination rather than the trace policy. Kaplan *et al.*'s model is extended to consider policies to respond to potential outbreak scenarios.

15. SUBJECT TERMS
cascading network, biological attack, homeland defense, mitigation planning, SIR model

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